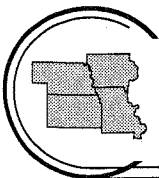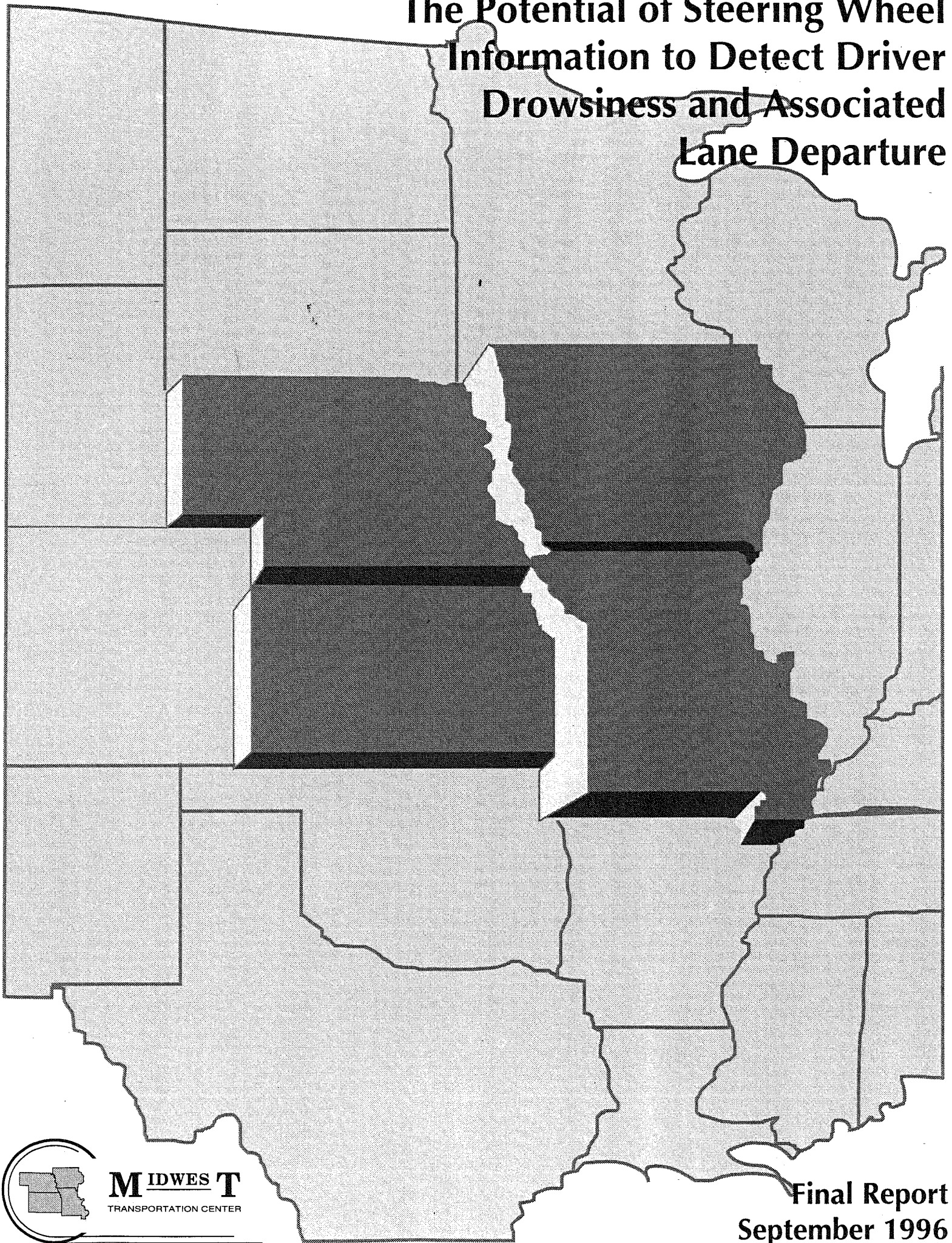# The Potential of Steering Wheel Information to Detect Driver Drowsiness and Associated Lane Departure

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TRANSPORTATION CENTER

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The Potential of Steering Wheel Information to Detect Driver Drowsiness and Associated Lane Departure

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ABSTRACT

This report summarizes research to date concerned with identification of drowsy drivers from information contained in steering wheel and lane position data. Data analyzed in this report was obtained from a Rockwell-Collins van driven on interstate and state highways in Iowa. Key results in this paper include:

- The type of steering wheel sensor can influence some of the more popular statistics promoted for drowsy driver identification

- Weather conditions have a strong influence on the same statistics

- Stochastic characterizations of steering wheel and lane position processes appear to have strong similarities

INTRODUCTION

Driver drowsiness is of major importance the U.S. transportation system. It is directly related to approximately 2 percent of all accidents, and is a factor in as many as 70-80 percent of single-vehicle accidents. Given that in 1986 trucking industry economic loss associated with accidents was approximately 9 billion dollars, assuming drowsiness as a factor of 10 percent of accidents, this represents 900 million dollars of associated economic loss, not to mention injuries and fatalities. The evolution of predictive safety devices, such as anti-lock brakes, as the logical extension of passive devices which are designed to minimize loss once an accident has taken place, has taken a dramatic upturn in the past two years. This is particularly true in Europe, where consortia involving countries and automotive companies are working together. The most notable consortium (DREAM) includes Mercedes, BMW, Volvo, Audi, Ford-Europe, and a spectrum of support institutions. One of their major focus areas is identification of driver drowsiness, which would be integrated with a "leaving the road" alarm/control system. In the U.S., major ongoing efforts in drowsy driver detection include a National Highway Transportation Safety Association (NHTSA)-sponsored project by Essex Corporation, and a steering wheel related effort at Virginia Technical University. Rockwell International (RI) is also involved, and in particular has been awarded funds from NHTSA to develop a "leaving the road" alarm system, based on their specially designed image collection/processing camera.[RI]

The motivation for this investigation stems from discussions with scientists at RI combined with our own efforts in this area for the past two years. A major hurdle in the development of their system is the question of when noting that the vehicle is leaving the lane, is it doing so intentionally. If so, then an alarm should not be sounded. If the departure is due to inattentiveness, which is very often caused by drowsiness, then it should be sounded. Since the RI market is the trucking industry, the potential for driver irritation caused by excessive false alarms is a major concern. Research for the past three years has involved the development of hardware and software to collect steering wheel motion, driver on-line assessment of drowsiness, and other potentially useful sensor data. This work was originally funded in part by the Ford Michigan Proving Grounds (MPG). The system was

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used to collect driver data at the MPG during the summer of 1993. The system was used in a 1993 driver study [MER]. In 1994, RI provided seed money to support development signal processing algorithms to enhance the performance of our own lane tracking system.

This report summarizes a continuation of the above efforts. A long term goal of this research is to establish a collaborative research program with RI, and in particular, with the Rockwell-Collins division in Cedar Rapids. Such a collaboration, combined with the presence of the National Automotive Simulator Facility at Iowa City, could make Iowa an internationally recognized venue for research and development concerned with automotive predictive safety systems. The development of a reliable driver drowsiness identification system with the ability to predict imminent lane departure is a nontrivial task, to say the least. But the impact of such a system on automotive safety and transportation systems would be significant. The most likely first application of such a system would be commercial trucking fleets. The payoff, particularly to those fleets who operate in the Midwest, where there are sizable distances between major cities, would be enormous. First, there would be the potential for reduced economic loss and improved safety, as noted above. A second benefit would be the development of a data base so that driver/route combinations could be optimized to minimize the potential for drowsiness-related accidents.

One goal of the research program discussed in this report was to assess the potential of the joint stochastic information contained in steering wheel and lane position data for identifying trends in drowsiness and for predicting imminent lane departure associated with the same. This assessment was in relation to the RI imaging system, which appears to be one of the main contenders for use in lane departure detection. A second goal concerned identification of hardware and software issues which could improve that system's performance. A third goal was to investigate the potential value of the stochastic structure of lane position and steering wheel position data, relative to the more commonly studied summary statistics. Such statistics, by their very nature, de-emphasized detailed correlation which may be present between these two processes. Finally, it is worth noting that the efforts discussed in this report utilized alert drivers, for the most part, since the safety issues associated with the use of drowsy drivers would require an automotive simulator. Not only would such a simulator be costly, but one would also have to validate results in relation to on-road systems. No published results along these lines have been found to date. Moreover, we believe that such a expensive effort would be difficult to justify at the present. The premise of the research described in this report is that there are significant issues involving characterization of alert drivers and of the driving environment that deserve attention prior to addressing the issue of drowsiness.

PROPOSED TASKS

The tasks outlined in the proposal, upon which this report is based, are highly multidisciplinary in nature. Four graduate students were involved in this effort.

1. A Department of Statistics student to critically evaluate the value of steering wheel summary-statistics (e.g. mean, standard deviation, skew, ANOVA, discriminant

analysis) which are the traditional tools used by researchers to extract drowsiness information. The robustness of these measures to the violation of the underlying regularity conditions upon which they are based is a major element of this evaluation.

2. An Electrical Engineering student to investigate the potential of signal processing tools, as alternative to the standard statistical tools, and for improved lane tracking in adverse conditions.

3. A Computer Engineering student to investigate the influence of vehicle, sensor, driver and data acquisition procedure, and track configuration on the steering wheel signal, as well as derived information.

4. A Computer Engineering student to implement a high performance, low cost image frame grabber board with the ability to perform on-board processing to enhance lane position information.

The academic study areas of these students are very complementary, and are all essential for achieving a reliable drowsiness identification system. Our analysis of the Michigan Proving Grounds (MPG) data had previously dramatized the need for such a multi-disciplinary approach. For example, we discovered that the stochastic structure of the steering wheel signal is strongly influenced by the straight versus curved nature of the track. How this influence is reflected in summary statistical information is discussed in this report, but this issue is still under investigation. What is known is that practically all published results along these lines process steering wheel data without regard to the track configuration. Another issue is related to data pre-processing. By failing to remove the slowly varying mean component of the steering wheel data, the information in the key frequency range 0.1-0.3 Hz can be highly contaminated, as can any other frequency-related information (e.g., steering wheel reversal rate, which is one of the most popular measures of drowsiness). Because the overwhelming majority of researchers in this area are not well versed in signal processing, we believe that, based on our analysis to date, our approach is essential toward developing reliable measures of drowsiness.

Our approach in the effort described in this report represents a continuation of our multi-disciplinary approach to the drowsy driver problem. The specific proposed tasks related to this research effort included:

Task 1: Development of the required data acquisition system
Task 2: Specification of the experimental design
Task 3: Collection of data under prescribed test conditions
Task 4: Data Analysis
Task 5: Final Report

The analysis in task 4 was to proceed by investigating the data sets with respect to three issues. One issue is concerned with how sensor and data acquisition parameters might influence traditional summary statistics used in identification of driver drowsiness. The

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second addresses how driving environment might influence the same statistics. The third is based on the possibility that summary statistics may not contain all of the potentially useful information in characterizing the driver's state. Hence, the data is studied from the viewpoint of a stochastic process.

RESULTS RELATED TO TASKS 1-3

This section summarizes the major results related to the above tasks 1-3. The results of the fourth task are presented in the next section, as they represent the most involved and multifaceted component of the research effort.

Development of the Required Data Acquisition System

The data acquisition system was proposed to include (i) a multi-sensor steering wheel-motion measurement system, and (ii) an image-based lane tracking system. The latter system is still under development. For this reason, the results in this section will be restricted to the steering wheel system. These results are described in detail in Chapter 4 of [BR]. They are also the subject of an invited presentation [BRS]. A schematic of the required data acquisition system is shown in Figure 1. It includes a personal computer with an analog-to digital (A/C) acquisition board, sensor interface hardware, and three different steering wheel sensors. The special needs of this system, such as real time simultaneous acquisition, the need for well matched anti-aliasing filters, and the ability to detect and correct acquisition errors in a harsh automotive environment, required extensive development of customized hardware and software. The hardware requirements of this system were:

1. Simultaneous digitization of four analog channels
2. Matched anti-aliasing filters for each of two types (An anti-aliasing filter is an analog low-pass filter that does not permit high frequencies out of the range of interest to alias themselves as lower frequencies once the data has been sampled.)
3. Acquisition of one digital channel
4. Synchronization between 1 and 3

All of these requirements were satisfied. In addition, the developed system was able to perform a fast sampling averaging procedure to reduce the influence for noise contamination. Specific sensor arrangements included:
- Wirewound potentiometer with Butterworth anti-aliasing filter
- Wirewound potentiometer with Bessel anti-aliasing filter
- Thin film potentiometer with Butterworth anti-aliasing filter
- Thin film potentiometer with Bessel anti-aliasing filter
- Digital optical encoder

A Butterworth filter minimizes the energy outside of the frequency range of interest, while a Bessel filter minimizes distortion within this range. Both filter types are commonly used.

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All analog data are acquired at 12 bit resolution, resulting in approximately 0.25 degrees of precision. The digital encoder has approximately twice the precision of the analog channels. All data are sampled approximately 25 times per second. Previous research has shown that this is more than sufficient to accurately measure the steering motion of a human driver.

Specification of the Experimental Design

The experimental design of this effort was arrived at through joint discussions with RI personnel both at the Collins division and at the Des Moines Science Center. Table 1 lists issues associated with each aspect of the project. These issues were investigated in relation to their affect on a variety of commonly used summary statistics related to steering wheel and lane position.

TABLE 1 Issues Addressed in Relation to Each Effort

Data	AA filter type (Chebychev vs. Butterworth)
Acquisition	sensor type (wire vs. film vs. encoder) post filter (with vs. without)
Driving	road lanes (2 vs. 4)
Environment	road condition (dry vs. wet) time of day (day vs. night)

Data Collection

Data collected for this investigation were obtained primarily from an instrumented van supplied and driven by RI personnel. Included were steering wheel data associated with the system discussed in section 3.1, and lane position information collected by the RI camera. This requirement of two data acquisition systems necessitated special care in logging and periodically recalibrating the clocks of the two computers. Data were collected for approximately two to four hours for each of the eight possible driving environment conditions listed in Table 1. Additionally, the driver was polled at random intervals as to his level of drowsiness, and comments related to changes in the driving environment (e.g., changing lanes or being passed). This data acquisition effort required that Iowa State University and RI Collins Division researchers coordinate schedules over a period of approximately two months. A lesser amount of data was provided by a second RI test van which traveled across the U.S. This data was supplied only more recently, so that it has received less attention to date than the other data.

DATA ANALYSIS

Analysis of the data included three major components:
- evaluation of data acquisition factors on steering wheel summary statistics
- evaluation of the driving environment on both steering wheel and lane position summary statistics

- investigation of the stochastic nature of steering wheel data

The major results in each of these three areas are now summarized.

Data Acquisition Influences on Summary Statistics

The summary in this subsection is taken from [BR] (pp.80-82). For more detailed information the reader is referred to chapters 5, 6 and 7 of [BR]. The statistics studied included:

1. Standard deviation of steering wheel position (SDTSTR)
2. Reversal rate (0.5, 1.0 and 2.0 degree gap sizes) (SRR)
3. Mean steering velocity (MEANVEL)
4. Standard deviation of steering velocity (STUVEL)

For each statistic, the influences of the following sensor-related parameters were studied:
- Sensor resolution
- Anti-aliasing (AA) filter type
- Sensor type
- Pre-processing in the form of noise removal

The analysis began by computing each statistic on data obtained from a variety of sensors. Various preprocessing effects were performed to reduce (effective) sensor resolution, remove noise spikes, etc., to produce a set of signals which would allow us to investigate the effects of each of the parameters of interest. A simple hypothesis test was used to determine if the mean of two signals is equal to zero indicating that the signals are equivalent and the associated parameter has no influence.

Results of this test indicated the following:
- Sensor resolution has a quite large effect on the means of steering reversal rate and standard deviation of steering position statistics, and has a minimal influence on the means of the other statistics.
- Anti-aliasing filter type has little to no direct influence on the mean of any of the statistics we studied.
- Sensor type also has a relatively small influence on the means of these statistics. The influence is generally larger than that for the anti-aliasing filter type but is still quite small.
- Pre-processing technique has a large influence on the means of all the statistics except standard deviation of steering position.

Because driver drowsiness monitoring often involves percent changes in statistics, rather than absolute value, the statistics whose means were most affected by parameter changes were studied to determine the effects of these parameters on the percent changes. The results of this portion of the research are summarized below.

It was not the purpose of this research to determine when a driver is falling asleep, nor to select appropriate statistics for monitoring of driver behavior. The primary goal was to

determine which (if any) of the parameters listed earlier have a significant influence on typical driver drowsiness statistics and to attempt to isolate those parameters which require a more detailed investigation. To that end the following conclusions and recommendations were derived:

1. The study of steering reversal rate showed that the influences of many of the parameters are dependent to some degree on the gap size over which the reversals are measured. While a certain amount of research has been done to investigate the effects of gap size, no published results which examine joint influences of sensor resolution and gap size were identified. This work showed that these two parameters are somewhat correlated, so that any investigation of the effects of gap size should simultaneously address the effects of sensor resolution.

2. Velocity related statistics are highly influenced by high frequency components. This result is important for two reasons. First, the need to examine the frequency characteristics of the steering data cannot be overemphasized. If strong high frequency components are present in the signal, any velocity statistics will likely be contaminated. This relates to the observation that different statistics appear to have different requirements in terms of the characteristics of the input signal. Thus, pre-processing techniques may need to be developed for each statistic to produce the optimum results.

The Influence of the Driving Environment on Joint Statistics

Summary statistics were utilized to investigate characteristics of the steering wheel and lane position data. Interesting features that can be measured with summary statistics include:

1. Variability of the steering wheel and lane position
2. Steering wheel and lateral reversals (changes in direction)
3. Steering wheel and lateral velocity

Table 2 gives a list of the summary statistics that were used in this data analysis.

These statistics were largely derived from other sources, where they have been used for such purposes as drowsy driver detection. They include those studied in section 4.1, plus a variety of others. Standard deviation of steering angle and standard deviation of lane position measure variability of the steering wheel and lane position data [WB]. Steering reversals (1 degree), steering reversals (5 degrees), lateral reversals (10 degrees), and lateral reversals (30 degrees) measure reversal rates, i.e., how often the steering wheel or lateral motion changes direction by at least a certain amount, known as the gap size. For the steering wheel data, the one degree gap size was used because of its success in distinguishing alert and drowsy data from an earlier study [ES], while the five degree gap size reflects the fairly wide range of steering wheel motion observed for the data analyzed here. The choice of gap size for the lateral reversal rate was more arbitrary, as there is relatively little information on this statistic. A number of statistics related to steering wheel and lateral velocity (e.g., [SW]) were analyzed. These range from mean and standard deviation measure (standard deviation of steering velocity, mean lateral velocity, standard deviation of lateral velocity) to measures of low velocity steering and transitions between low and high velocity steering (low velocity

steering, steering velocity reversals, mean low velocity). Lane edge time approximated the proportion of time the vehicle spent outside the lane boundary [WW], which in fact could only be approximated, since the lane position camera did not accurately record when the vehicle exceeded the lane boundary.

TABLE 2 List of Summary Statistics Considered in Summary Statistics Analysis

standard deviation of steering angle
steering reversals (1 degree gap size)
steering reversals (5 degree gap size)
standard deviation of steering velocity
low steering velocity (fraction of time less than 2 degree/second
steering velocity reversals (transitions between low/high velocities)
mean low velocity (mean duration @ low velocity steering)
standard deviation of lane position
lane edge time (fraction of time within 5 cm of lane marker)
mean lateral velocity
standard deviation of lateral velocity
lateral reversals (10 cm gap size)
lateral reversal (30 cm gap size)

Data Description

Three days of road data were used for the analysis, March 1, 3, and 6, 1995. Each day's data consisted of about 80 minutes of 65 mph, four-lane driving, starting from Cedar Rapids, Iowa on I-380 N for approximately an hour, and then continuing on HW-20 E at the same speed. Weather conditions for the three days were as follows:

    Day 1 — sunny with 15 mph wind
    Day 2 — sunny
    Day 3 — cloudy, foggy and wet roads

The driver reported some drowsiness the first 30 minutes of Day 1 and from 30 to 80 minutes on Day 2. Other observed driving conditions were similar on the three days. Four data processing conditions were applied to the steering wheel and lane position data, no process, downsampling, and high-pass and low-pass filtering. Downsampling entails using every m^{th} data sample. For example, if m=5, then only every fifth sample is used for analysis. This procedure is used if it is desired to reduce the frequency range of interest. For example, the data was originally sampled at a rate of 25 samples/second, allowing an analysis range of 0-10 Hz. However, most published results in this area use a range 0-2 Hz. To achieve this lower frequency range the data was downsampled by a factor of 5. To investigate the relative amount of useful information in very low (>0.5 Hz) the data was run through a low-pass filter with a cut off frequency of 0.5 Hz. The output of this filter is referred to as low-pass filter

data. The difference between this data and the original data is referred to as high-pass filter data. Each of these is detailed in Table 3.

TABLE 3 Data Processing Conditions

	Condition	Sample Rate (Hz)	Cutoff Frequency
Steering Data	Unprocessed	25.7	-
	Downsampled	5	-
	High-pass filtered	5	0.05
	Low-pass filtered	0.5	0.05
Lane Position Data	Unprocessed	variable (19.6 avg)	
	Downsampled	5	-
	High-pass filtered	5	0.05
	Low-pass filtered	0.5	0.05

The effects of these different data processing conditions were investigated with regard to:
  i. the influence of driving conditions
  ii. the relationship between the steering wheel and land position data

Methods of Analysis

The data contained at least three potentially influential factors:

1. Day factor, i.e., the influence of particular days, caused by the weather conditions, or perhaps the mood of the driver
2. Road factor (I-380N vs. HW-2O E)
3. Driver alertness factor (alert vs. drowsy)

(A further note on the day effect: if driving conditions across days were similar, this factor could be used to verify repeatability of summary statistics across days.)

These factors could possibly interact, meaning the size of one factor's level depends on another factor's level, so interactions were also considered. The value of a summary statistic, then, could be modeled as the addition of all these effects plus a random error: $y(ijkl) = d(i) + r(j) + a(k) + dr(ij) + da(ik) + e(ijkl)$, where y = summary statistic, d = day, r = road, a = alertness, and e = random error. Notice only the day*road (dr) and day*alertness (da) interactions were included as these were the only interactions that could be estimated given the combinations of factors observed in the data.

Of interest was how the size of a given factor depended on its level. For instance, was there any difference in the day effect across different days? If not, then the day factor could be viewed as insignificant, since it would be constant regardless of the particular day. Statistical hypothesis testing provided the framework for testing a null hypothesis: no differences in the levels for a given factor vs. an alternative hypothesis: some difference in

levels. As an example, for the day effect, the test was HO: d(1) = d(2) = d(3) vs. HI: not all equal.

Under certain distribution theory, one can derive a p-value from the observed data. The p-value measures the level of support for the null hypothesis; it is a probability value related to the observed data under the null hypothesis. A small p-value (such as 0.05) indicates little support for the null hypothesis, in which case the action is to reject the null hypothesis in favor of the alternative hypothesis. This means that the factor in question is significant, i.e., the data support differences in the levels for that factor.

The hypothesis testing involved two methods: Multivariate analysis of variance (MANOVA) and univariate analysis of variance (ANOVA). Essentially these methods describe the variability of summary statistics, in particular, how much of the variability can be attributed to differences in levels of particular factors. Based on this variability information, the (M)ANOVA yields hypothesis tests of the form mentioned above. MANOVA was used to test factors for a number of summary statistics simultaneously, which answered the general question of whether the summary statistics as a whole supported the significance of a factor. To test factors for individual summary statistics, ANOVA was used. Only the steering wheel statistics were considered for the (M)ANOVA, as the lane position data is currently only available for Day 3.

To explore the relationship between steering wheel and lane position, a couple of other methods were utilized. One compared summary statistics and the other related the time series. To identify associations between the two groups of summary statistics, canonical correlation analysis was used. Canonical correlation analysis is a standard multivariate statistical method which seeks to quantify the association between two groups of variables by finding the maximum correlation, i.e., the strongest relationships between linear combinations from each group, the pairs of linear combinations are known as canonical variables, and their correlation are known as canonical correlation. Of interest in this analysis was the size of the canonical correlation and how each variable (summary statistic) contributed to the canonical variables.

To investigate the relation between the steering wheel and lane position time series, first a preliminary visual comparison was done. The visual comparison allowed one to find differences and similarities in the behavior of the two time series, which perhaps could be related to observed driving events, such as passing cars. Next, the cross correlation was examined, which measured the strength of the association between the time series.

Results

MANOVA was carried out using all the steering wheel statistics listed in Table 2. Table 4 summarizes the results of the MANOVA for each of the data processing conditions.

Hypothesis tests involving a statistic known as "Wilks' Lambda" were used to test the significance of the various factors, i.e., if levels were significantly different. The Day effect was always highly significant (p = 0.0001), except for the low-pass filtered data. Figure 2

shows steering reversals (S) for the first 30 minutes of Days 2 and 3. Recall the main difference between Days 2 and 3 was the weather conditions; sunny on Day 2, but cloudy, foggy, and wet roads on Day 3. The difference observed for days, then, may be mostly attributable to the effect of weather.

TABLE 4 MANOVA Summary (p-values)

Data	Day	Road	Alertness	Day*Road	Day*Alertness
Original	0.0001	0.0029	0.0208	0.0392	0.0001
Downsampled	0.0001	0.1499	0.0749	0.6648	0.0001
HP Filtered	0.0001	0.0654	0.0049	0.1276	0.0001
LP Filtered	0.1619	0.0595	0.3932	0.9597	0.0266

The significance of the Road effect ($p = 0.0029$ for original data) is perhaps unexpected, because there was little observed difference between I-38ON and HW-2OE, both being 4-lane, 65 mph roads. There may be subtle differences related to the road topography. For low-pass filtered data, the Road effect was the most significant main effect ($p = 0.0595$), and the low-pass filtered data is thought to be highly related to road topography, since its highest frequency component is 0.05 Hz.

The Day*Alertness interaction was highly significant ($p = 0.0001$) for all but the low-pass filtered data. Figure 3 illustrates this interaction for standard deviation of steering velocity on Days 1 and 2. The horizontal lines show the mean level at a particular road, alertness combination. The first two horizontal lines in each plot correspond to I-380N under different levels of alertness. The last horizontal line corresponds to HW-2OE. Drowsiness corresponds to the highest level on Day 1, but the lowest two levels on Day 2, i.e., the effect of driver alertness depends on the particular day.

It should be pointed out that any results involving driver alertness should be interpreted with care, since the driver's self-asserted level of alertness was used as the definitional measure. An improvement could be made by videotaping the driver's face with an on-board spy camera, and cross-validating signs of drowsiness seen on the videotape with the information obtained from the driver.

Table 5 gives results from the ANOVA for summary statistics which had significant road or driver alertness effects. No statistics are listed for the day effect, since this almost always had $p = 0.0001$. All of the statistics listed are related to velocity, except steering reversals (1). Interestingly, from an earlier analysis [ES], steering reversals (1) had a highly significant

alertness effect as well (p = 0.0001). However, as suggested earlier, any results related to driver alertness should be interpreted with some caution.

TABLE 5 ANOVA Summary: Significant Road and Alertness Effects ($\alpha = 0.05$)

Effect	Statistic	Data	p = value
Road	Steering velocity reversals	Original	0.0218
	Std. dev. of steering velocity	LP filtered	0.0467
Alertness	Steering reversals (1 degree)	HP filtered	0.0035
	Mean low velocity	HP filtered	0.0117
	Steering velocity reversals	Original	0.0279
	Low steering velocity	Original	0.0300

Next, we considered canonical correlation analysis. In the canonical correlation analysis, all of the summary statistics were used, except low velocity steering statistics for the low-pass filtered data. These statistics were practically constant, since the low-pass filtered data consisted of almost all low velocity steering. Hence, in this analysis any correlation involving low velocity statistics would have been meaningless, and so these statistics were not used. The low-pass filtered data, then, had the disadvantage of fewer steering wheel statistics, and this should be taken into account when comparing the results described below.

Table 6 summarizes the results for the first canonical variable; the pair of linear combinations of statistics that had the highest correlation. To judge the association between a canonical variable and a particular summary statistic, the correlation between the summary statistic and canonical variable was computed. The canonical correlation given in Table 6 measure the strength of the relationship between pairs of canonical variables, and consequently, between the steering wheel statistics and lane position statistics. The canonical correlation ranged from 0.4737 for the low-pass filtered data up to 0.7318 for the high-pass filtered data, indicating a moderate to fairly strong association between the steering wheel and lane position statistics. In each case, the steering wheel statistic most highly related to the canonical variable, based on the correlation information, was standard deviaition of steering angle, followed in most instances by steering reversals (S). For the lane position statistics, standard deviation of lane position and lateral reversals (30) were in general the two statistics most highly associated with the canonical variable.

Figure 4 shows the similar behavior of steering wheel statistic, St. dev. steering angle and lane position statistic. Lateral reversal (30) (correlation r = 0.5145), at least for certain time periods, e.g., between 40 and 55 minutes. The association of standard deviation of steering angle, steering reversals (5), lateral reversals (30) and standard deviation of lane position with the canonical variables suggests that the relationship between the steering wheel and lane position data may be most strong through larger amplitude movements in the data. This

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interpretation makes logical sense, since a large steering wheel movement will certainly affect the lane position, but a small movement, as might be measured by steering reversals (1), may have little or no effect on the lane position.

To investigate the correlation between steering wheel and lane position information, we used a time series approach. A 30 minute segment of data from Day 3 was used to assess correlation between the steering wheel and lane position time series. For this analysis it was necessary for the two data sets to be closely time coordinated, and observed time differences were well under one second. To compute correlation, the sampling rates had to exactly match. The lane position data, with its variable sampling rate, was transformed to a constant sampling rate of 20 Hz by linear interpolation. The steering wheel data was downsampled to 20 Hz by a technique involving zero-padding the Fourier transform, followed by an Inverse Fourier transform.

Figures 5 through 7 show two minutes of the original, high-pass filtered, and low-pass filtered data, respectively. In Figure 5 some of the larger peaks in steering wheel data, such as at 31.2 and 32.1 minutes, also appear in the lane position data. However, the large valley in the steering wheel data at 32.2 minutes, resulting a passing car event, does not appear to correspond well to the lane position data. This is because the camera was in the process of switching to track the center lane marker. Based on this visual inspection, then, the correlation structure seems to change with time, which perhaps depends on driving events.

Figure 6, the high-pass filtered data, shows another apparent difference in the two data sets, the steering wheel data has many more small peaks than the lane position data. These smaller peaks correspond to higher frequency steering wheel movement that is being filtered by the steering system. One area in which the high-pass filtered data appears to improve the correlation between the two data sets is at 32.2 minutes; a passing car event.

The low-pass filtered data, Figure 7, indicates that the low frequency steering wheel and lane position movements correspond fairly well for the first minute, in that peaks and valleys occur at about the same time points. However, during the passing car event, there is a time disparity: the large valleys in the two data sets occur about 0.2 minutes apart. Again, this points to the fact that when the camera switches to tracking a different lane marker the correlation between steering wheel and lane position data will be temporarily lost. This is quantified in Figure 8, which shows the cross-correlation between the steering wheel and lane position data, as computed over one minute intervals. This graph emphasizes the changing correlation structure, as well as showing differences between the different filtering conditions. It suggests that, except for passing conditions, the low-pass filtered data were most highly correlated.

Investigation of the Stochastic Structure of Steering Wheel Motion

This section summarizes our investigation of the steering wheel and lane position data as random a process. For further details the reader is referred to [GA]. The motivation for this approach is twofold. First, we are interested in the potential of a random process characterization to provide more detailed information than summary statistics. Except for

[MH] and [E2], we are aware of no published results which consider the use of stochastic process theory for analysis of drowsy driver data. Second, such a temporally detailed characterization would seem to be more appropriate for predicting sudden lane departure.

Table 6 Correlations Between Summary Statistics & Their First Canonical Variables

Steering wheel statistics:

Data

Statistic	Original	Downsampled	High-Pass Filtered	Low-Pass Filtered
St. dev. steering angle	0.7578	0.7353	-0.7389	0.6123
Steering reversals (1)	0.3066	-0.0932	-0.0481	-0.4036
Steering reversals (5)	0.7474	0.6655	-0.1975	0.5444
St. dev. steering velocity	0.5292	0.3441	-0.2285	0.2747
Low velocity steering	-0.4846	-0.2580	0.1968	-
Steering velocity reversals	-0.2905	0.0067	0.0083	-
Mean low velocity	-0.3150	-0.2387	0.1931	-
Canonical correlation	0.5544	0.4964	0.7318	0.4737

Lane Position Statistics:

Data

Statistic	Original	Downsampled	High-Pass Filtered	Low-Pass Filtered
St. dev. lane position	0.5400	0.6541	-0.6807	0.7755
Lateral reversals (10)	0.4998	0.3258	-0.2128	-0.1947
Lateral reversals (30)	0.5628	0.7865	-0.7287	0.5465
Mean lateral velocity	0.4353	0.4721	-0.3949	0.1465
St. dev. lateral velocity	0.2785	0.2362	0.1158	0.0772
Lane edge time	0.1828	0.7244	0.5674	0.8814
Canonical correlation	0.5544	0.4964	0.7318	0.4737

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Our characterizations are parametric in nature. The reason for this is again two-fold. First, it admits a parsimonious representation of the data which is computationally efficient. Second, it allows us to monitor changes in a relatively small number of parameters which contain information associated with the auto-correlation function in a compact way. Specifically, we chose to model these processes as time-varying auto-regressive (AR) processes. The parameters of a time-varying AR process can be efficiently estimated using a Kalman filtering approach. It can also be viewed as a problem in system identification, where the output of the system is the process being studied and the input to the system is a fictitious white noise process.

Data Environment and Pre-processing

The steering wheel motion is greatly affected by the fact that in a real-life environment it is a non-stationary process. For example, we have previously demonstrated varying spectral structure induced by curves versus straight sections of a road [GS]. Road curvature contributes low- frequency, high-amplitude components in the steering wheel motion. These low frequencies can have the effect of overwhelming amplitudes of higher frequencies. Therefore, low- and high-frequency regions must be separated before the high-frequency information can be analyzed. Spectral analysis of the steering motion data in [GS] has suggested that the high-amplitude, low-frequency components of the data are located in the frequency range of 0-0.03 Hz. Therefore, in this investigation we separated the steering motion data into two frequency regions using 8th order low- and high-pass Butterworth filters with cut-off and cut-on frequencies of 0.05 Hz. During the data collection, a sampling rate of 25 Hz was used. However, in order to reduce excessive correlation between adjacent sample points we found that downsampling is another important part of the data pre-processing. If the sampling rate is too high, the resulting frequency resolution is low, and important frequency information may be lost in the data model. Therefore, we downsampled the low-pass filtered component of the steering data with a sampling rate of 0.5 Hz, and the high-pass filtered component with a sampling rate of 5 Hz. The sampling rate of the high-pass filtered signal was determined after the spectral analysis in [GS] suggested that steering motion energy is concentrated in the frequency region of 0.1- 2.0 Hz. This has also been observed by [MH].

High-Pass Filtering of Steering Wheel Motion Data

Figure 9 shows the steering wheel motion as a function of time for fifteen minutes of data on March 1st, 3rd and 6th. The steering motion shown used the 15 minute point as the starting point of the analysis since the vehicle entered the interstate a few minutes earlier. On these plots the low-frequency components originating from the road curvature can easily be seen. The high-pass filtered versions of these plots are seen in Figure 9. Comparing Figures 9 and 10, it can be seen that the higher frequencies are of lower amplitudes than the lower frequencies. Another interesting characteristic of the high-pass filtered steering motion is that the dynamic range of the steering motion is considerably smaller on March 6th, which is the foul weather day. This reduction in dynamic range may be caused by a more careful way of driving, due to the foul weather.

Before we can use the Kalman filter for time-varying system identification, we have to determine an appropriate model order. By using Akaike Information Criterion (AIC) and by estimating the auto-correlation function of the residuals of the AR model (see e.g., [MA]); we found that an AR (6) model fits the data fairly well. The Kalman filter was turned on at time $t = 15$ minutes, and the system parameters were estimated recursively up to time $t = 30$ minutes. Figure 11 shows recursive estimation of the first two AR parameters for all three days. The irregular behavior of the estimated AR parameters, $\hat{a}_1$ and $\hat{a}_2$, during the first two to three minutes is due to the initialization of the Kalman filter. From Figure 11 it can be seen that after the Kalman filter is initialized, $\hat{a}_1$ takes on values in the range (1.2,1.5), and $\hat{a}_2$ in the range (-1.2,-.85) on all three days. The remaining four AR parameters showed similar robustness with respect to day. The recursively estimated variance of the innovations is shown in Figure 12. From this plot it can be seen that the innovation variance on the foul weather day is considerably lower than on the fair weather days. This observation also corresponds to the low dynamic range of the amplitudes of the high-pass filtered steering wheel position of March 6th seen in Figure 10. This analysis suggests that the weather condition may have a notably stronger influence on the amplitude of the steering wheel motion than on its stochastic structure.

Comparison of AR Process Models of Steering Motion and Lane Tracking Data
This section compares the poles of the AR models of the high-passed steering motion and lane tracking data. Figure 13 shows the high-passed lane position data as a function of time on March 6th for the same time frame and section of I-380 N as addressed above. The circled sections of data in this plot are non-valid due to errors in the data collection, and were ignored in the analysis. First, it was necessary to determine what kind of pre-processing was appropriate in order to compare system parameters. To this end, it was found that the high-amplitude lower frequencies of the lane position data are located in the frequency region 0.01 - 0.1 Hz. This region includes the large scale steering wheel motions due to the road and not the driver. Therefore, the lane position data was high-pass filtered at a cut-on frequency 0.2 Hz. Next, the lane position data was downsampled to a sampling rate of 5 Hz. It was then found that an AR (6) model also fitted the resulting lane position data fairly well. This is significant, as it suggests that the level complexity of stochastic structure is perhaps maintained as the steering wheel motion is transferred through the steering system to the wheels.

Again, the Kalman filter was used to estimate the AR-parameters. Figure 14 shows the magnitude and phase of the poles both for the steering wheel motion and the lane position data on the same plots. As can be seen, both the magnitudes and phases of these two processes are very similar, indicating that the stochastic models of the steering motion and lane tracking data are fairly similar. Another interesting observation is that all three poles are complex for both processes. A complex pole contributes with an oscillatory component in the process, where the frequency is determined by the poles phase. The phases of the three poles have values fluctuating around 0.2, 1.2, and 2.2 radians, which reflect oscillatory behavior around the frequencies 0.16 Hz, 0.95 Hz, and 1.75 Hz.

CONCLUSIONS AND RECOMMENDATIONS

The following is a summary of conclusions related to this multi-disciplinary research effort. For more detailed discussion the reader is referred to [BR] and [GA].

i. The type of steering wheel position sensor can have a significant influence on commonly used summary statistics associated with drowsy driver detection; this is especially true of reversal rates.

ii. Weather conditions may significantly influence summary statistics, as well as the underlying steering wheel and lane position processes. This was supported by strong differences between data collected on sunny versus rainy days. Interestingly, the significant stochastic difference was limited to amplitude (less steering wheel position amplitude in rainy weather), and not so much in stochastic structure.

iii. Steering wheel and lane position processes exhibit a measurable amount of correlation. Lowpassed processes had generally higher correlation than high-passed processes. However, the high-passed processes exhibited reasonably strong stochastic similarities, as reflected on model parameters.

These conclusions have a number of significant implications regarding the development of a drowsy driver detection system. For example, not only does (i) imply that such a system should be designed with a particular sensor and processing technology in mind, even more importantly, it suggests that current ongoing research may lead to detection algorithms whose performance is adversely influenced by the type of sensor and processing techniques being used. It could also be, at least in part, responsible for some of the conflicting results obtained by different researchers. Conclusion (ii) has implications as serious as (i). In particular, the influence of a real world driving environment, including not only weather, but also road topography and time-of-day factors is significant. The vast majority of refinement of drowsy driver detection algorithm development has taken place in simulator environments, with no accounting for, or evaluation of, these influences. Hence, it is entirely possible that such influences could severely degrade the performance of such systems. Finally, the correlation analysis conclusion (iii) brings out a number of issues. First, at least in low frequency regions the above conclusion points to the redundancy of information. In this region it is in fact likely that the road topography plays a major role. For example, if the road curves, the mean steering wheel position will change. And since many drivers tend toward one side of the lane or the other in a curve, the lane position will also change. This redundancy not only suggests the lack of need for one or the other sensor in this frequency band, it also highlights the fact that road topography influence on drowsiness detection algorithms will be effected by not one but two data types. Hence, any regression variables based on these (and there are many) could combine to severely degrade the algorithm performance. All of these points provide evidence for the need for future research before a reliable drowsy driver detection algorithm can be realized. The following are some of the most important recommendations, based on the research summarized in this report:

1. Development of a standard data acquisition protocol.
   This would reduce the variability of findings among various researchers. It will require an in-depth investigation of the frequency content associated with the driving environment. In particular, the amount of valuable information in various ranges will need to be quantified. In all likelihood, such a protocol will have to account for a variety of vehicle dynamics, at the very least.
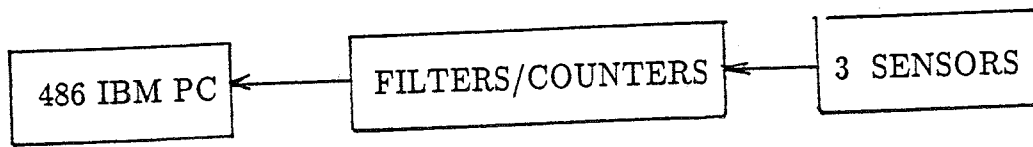
2. Quantification of Driving Environment Influence
   To date, the results in this report are the only ones we are aware of that address the influence of the driving environment on drowsy driver summary statistics. Our research has shown that these influences not only affect summary statistics, but they alter the basic stochastic structure of the underlying data. To be able to quantify these influences could result in significant improvement in detection performance by accommodating them.

3. Investigation of Stochastic Correlation Between Steering Wheel and Lane Position Processes
   There is currently a significant amount of ongoing research in the development of lane tracking devices. Because they are, for the most part, camera-based, they are significantly more expensive, in terms of both equipment and computing requirements, than steering wheel measurement systems. Our research suggests that at least in low frequency regions the information contained in lane position data is redundant, if one has steering wheel position data. At high frequencies there is less correlation. This is not surprising if one considers the complexity of the physical system (rack/pinion, suspension, wheel/road interface). By investigating the frequency-dependent correlation between lane position and steering wheel position data, it may be possible to design reduced cost lane tracking devices which focus on only a limited band of frequencies. At the very least, such an investigation would lead to a better idea of how information in one relates to information in the other, and how information in both jointly influences drowsiness detection algorithm performance.

FIGURE 1 (a) Basic Components of the System;
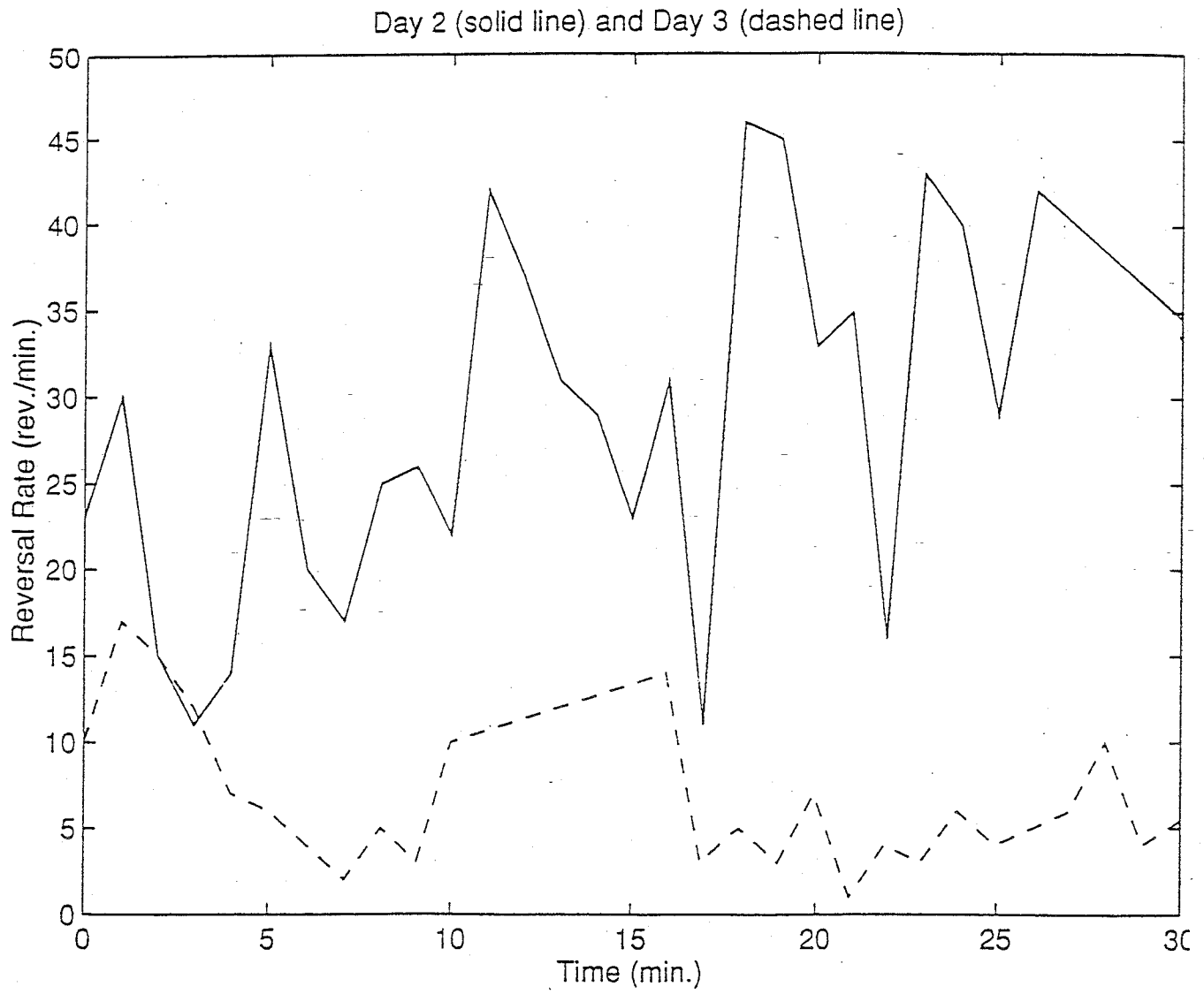**(b) Components of the Filter/Counter Unit**

```
┌──────────────┐      ┌─────────────────┐      ┌──────────────┐
│  486 IBM PC  │◄─────│ FILTERS/COUNTERS│◄─────│  3  SENSORS  │
└──────────────┘      └─────────────────┘      └──────────────┘
```

(a)

```
                  ┌──────────────────┐   ┌──────────┐   ┌────────────┐
from host         │  COMMUNICATION   │   │ CONTROL  │◄──│ AA FILTERS │  from
            ─────►│    PROCESSOR     │◄──│  LOGIC   │   │            │  analog
software          └──────────────────┘   └──────────┘   └────────────┘  sensors
                                              ▲
                                              │                          from
                                              └──────────────────────────
                                                                         encoder
```
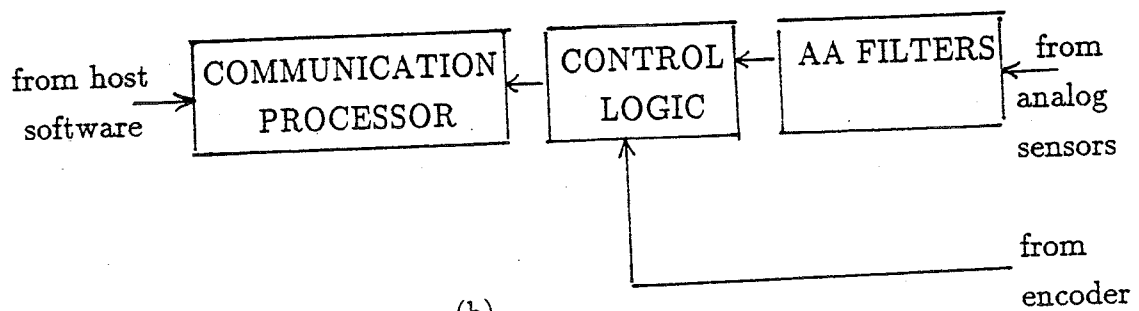
(b)

FIGURE 2 Day Effect for Steering Reversal (5 degrees)

Day 2 (solid line) and Day 3 (dashed line)

FIGURE 3 Interaction Effect for Standard Deviation of Steering Velocity
(--Indicates Drowsiness)

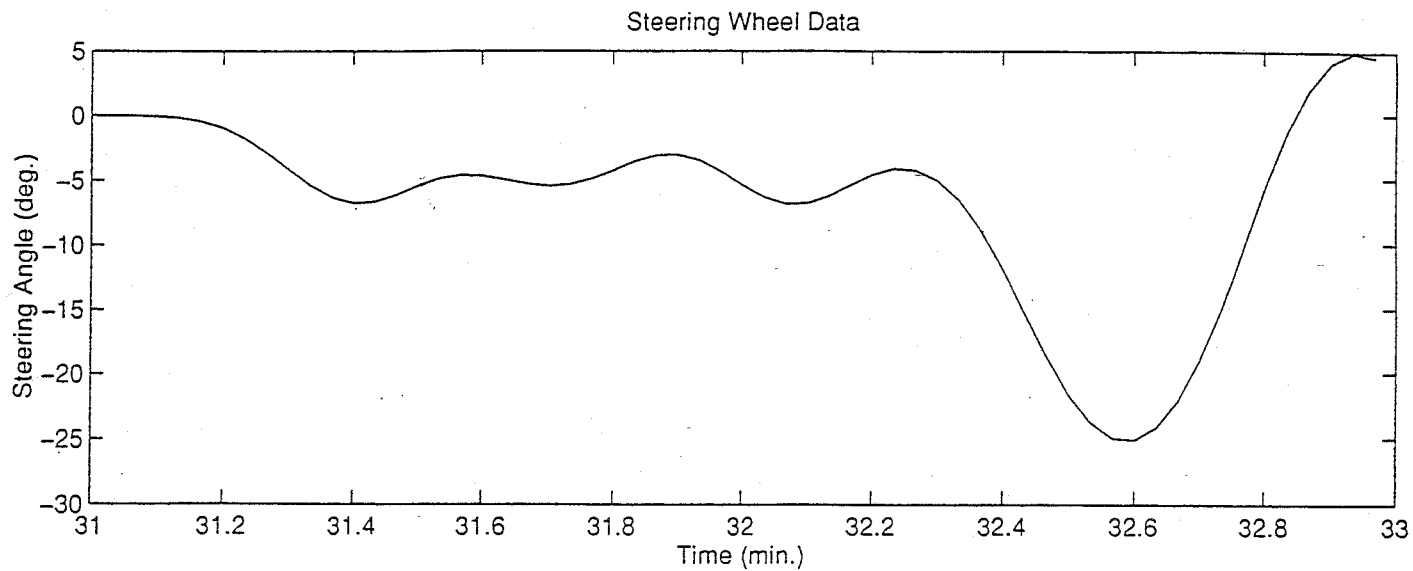Day 1
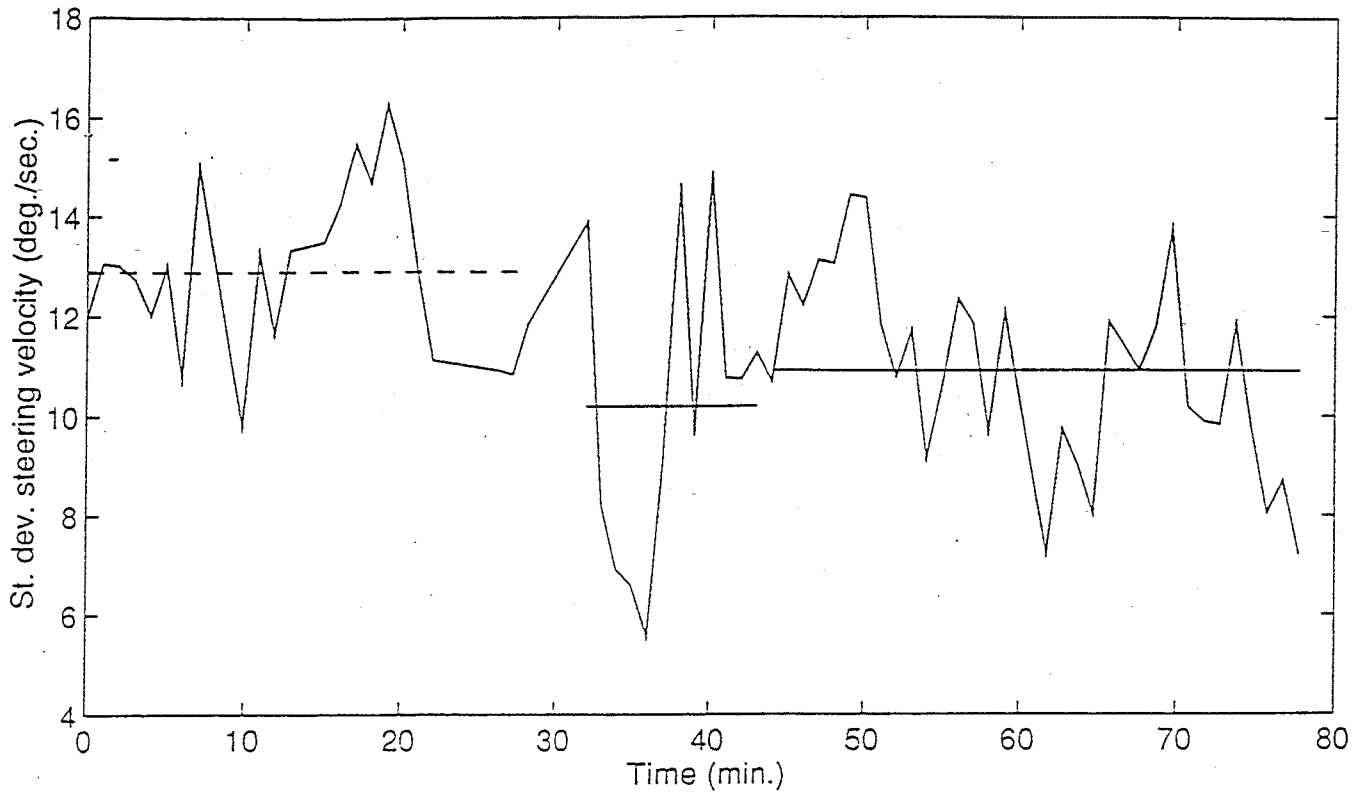
Day 2
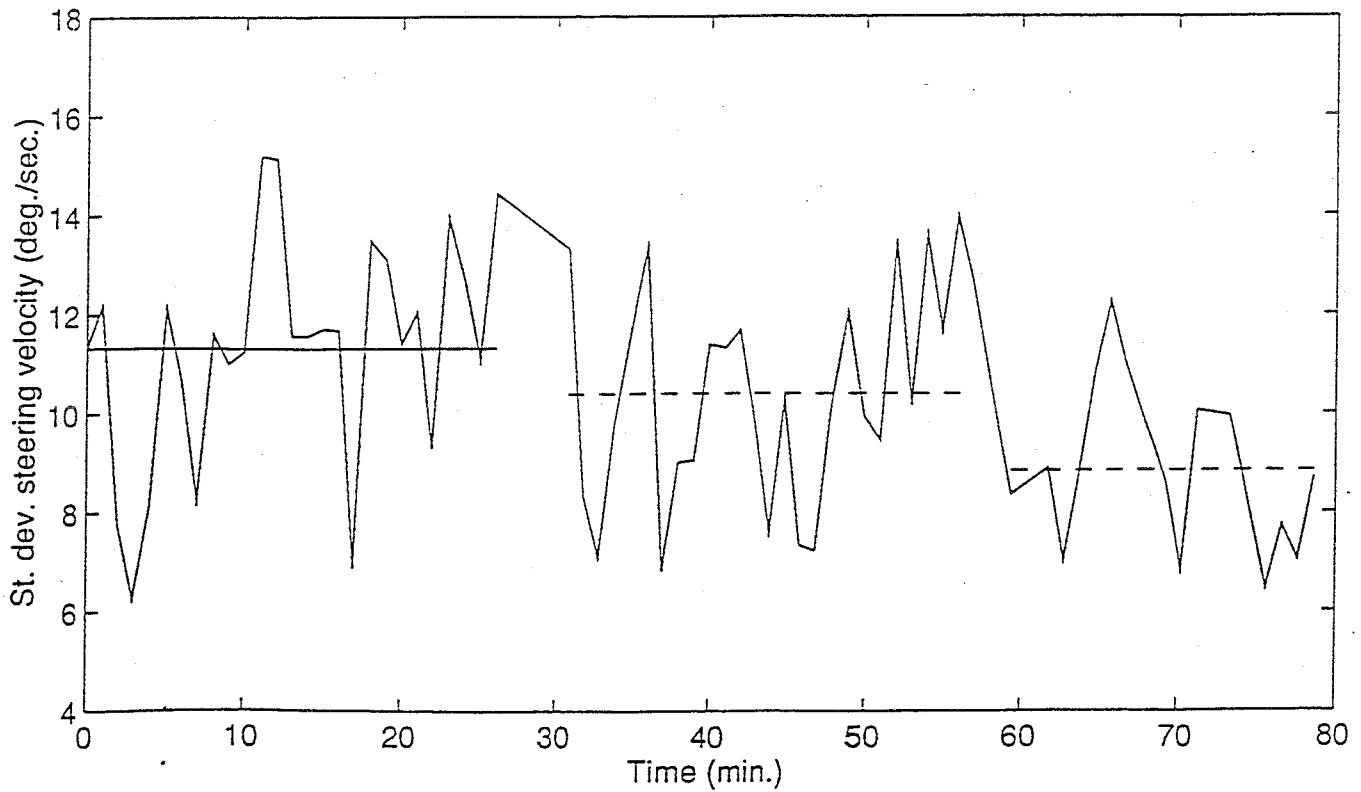
FIGURE 4 Correlated Summary Statistics (HP Filtered Data)

St. Dev. Steering Angle (–) vs. Lateral Reversals(30) (---)
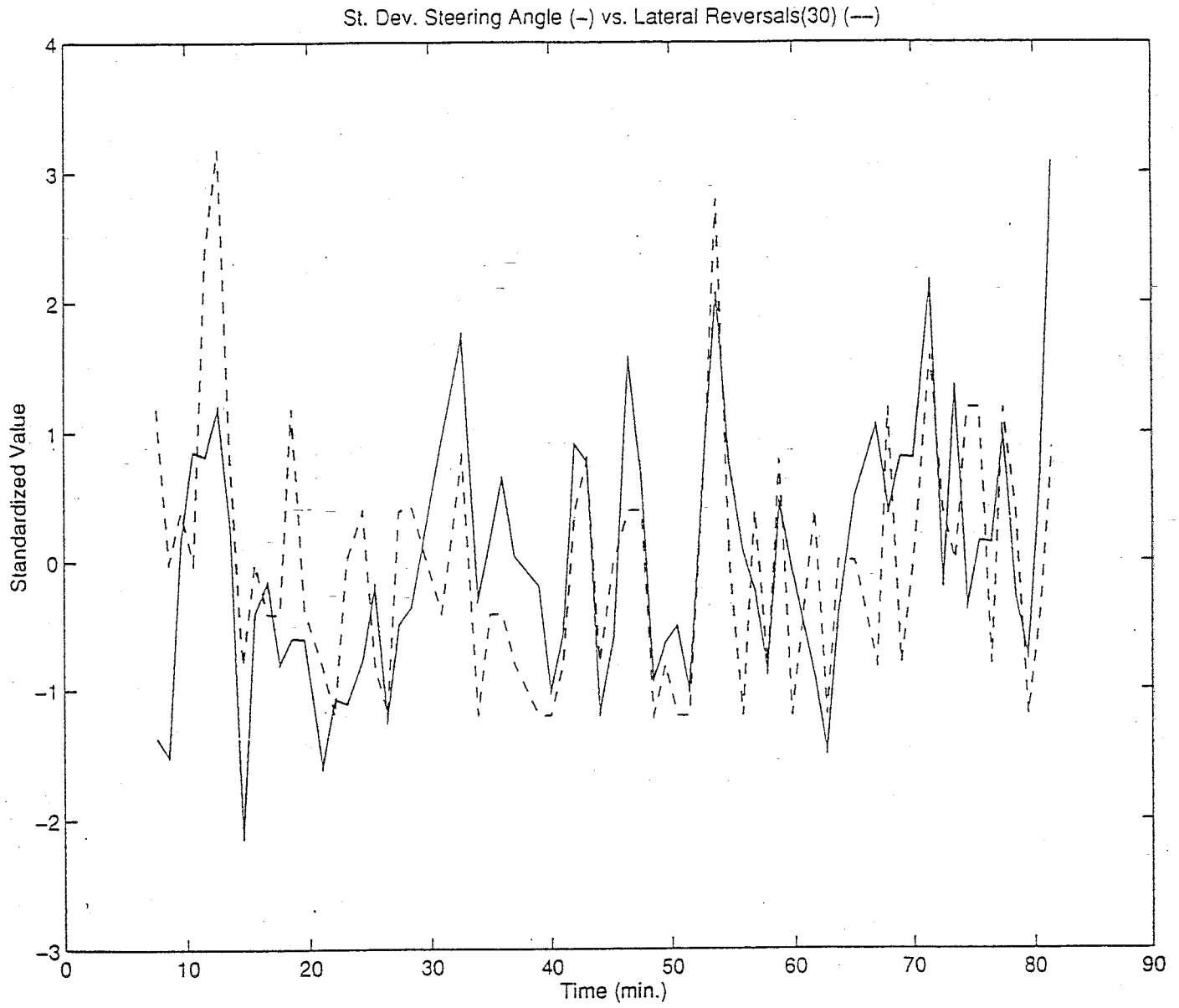
FIGURE 5 Original Steering Wheel and Lane Position Data

Steering Wheel Data
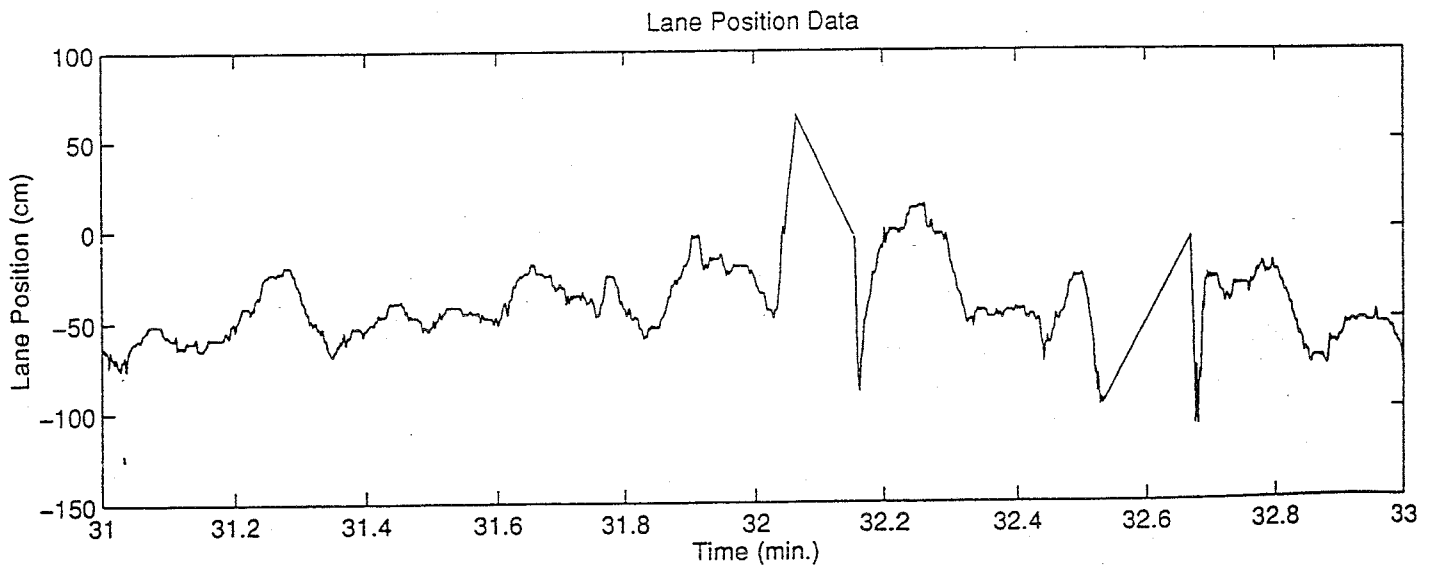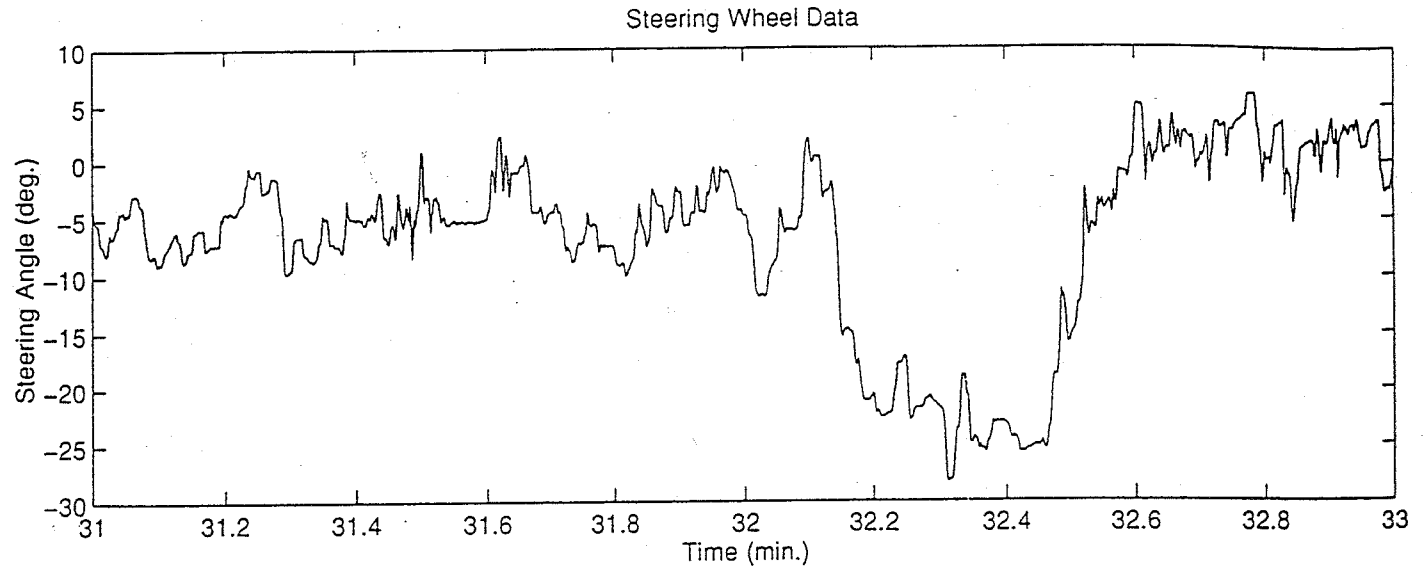
Lane Position Data

FIGURE 6 HP Filtered Steering Wheel and Lane Position Data

24
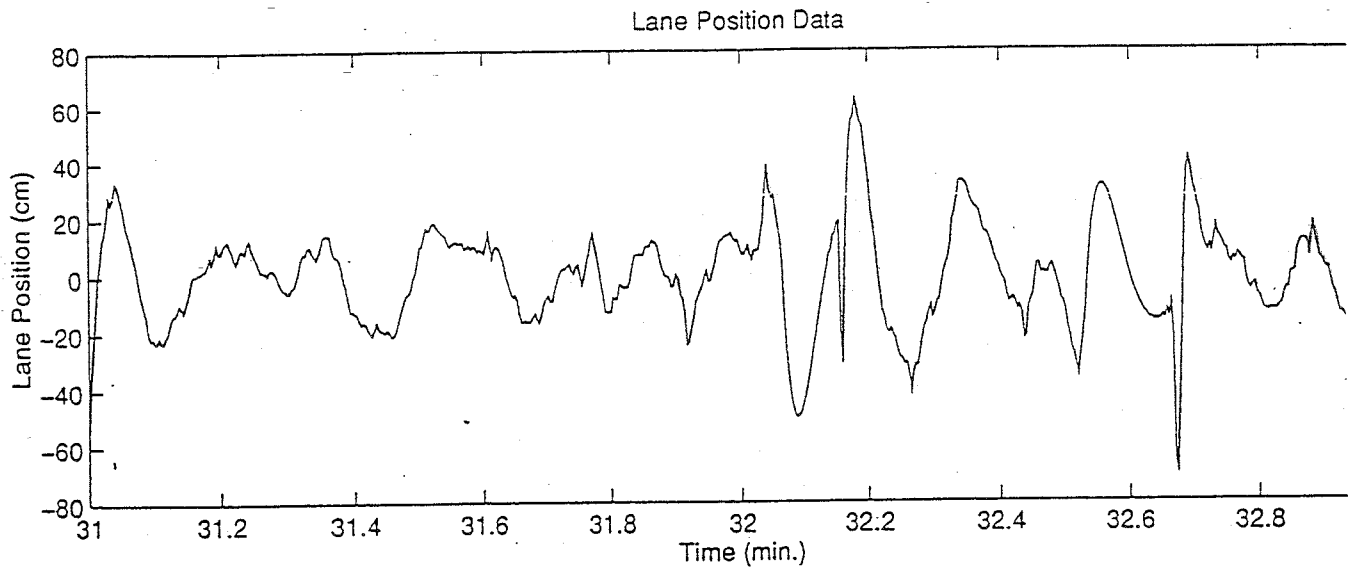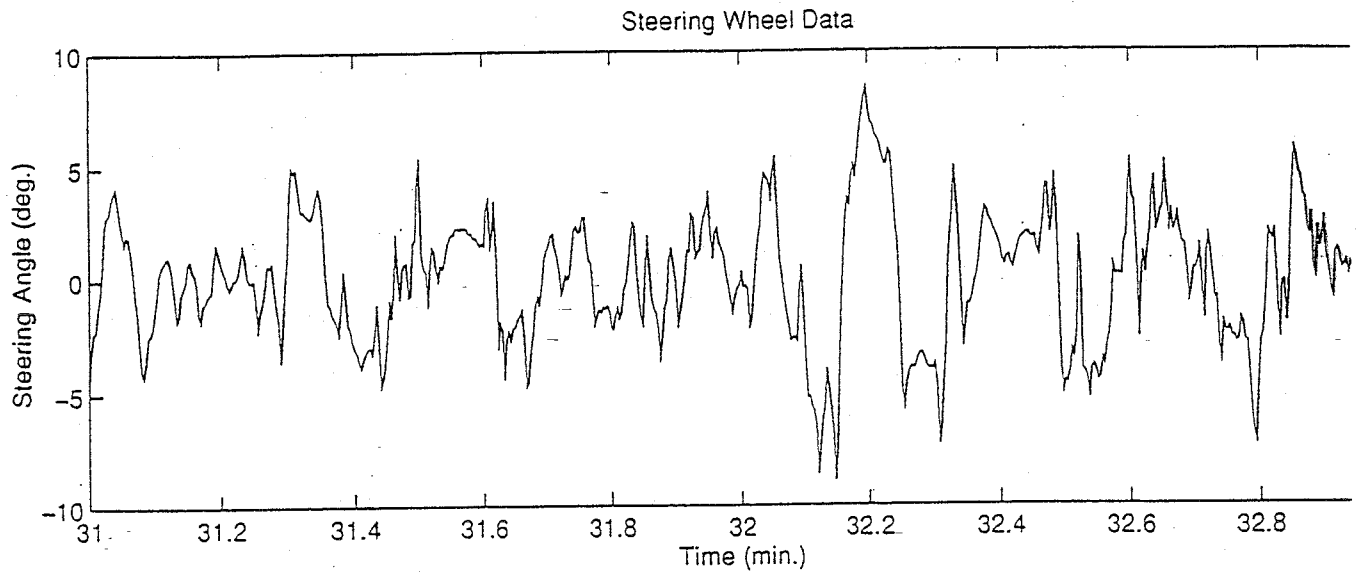
FIGURE 7 LP Filtered Steering Wheel and Lane Position Data

Steering Wheel Data
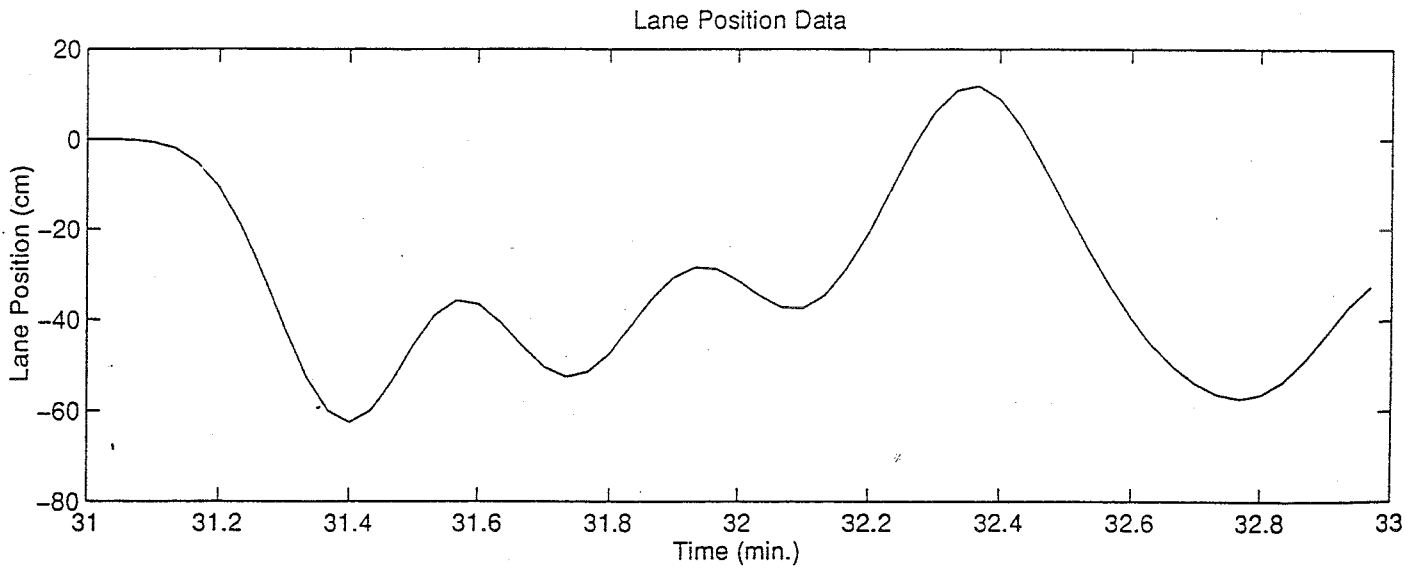
Lane Position Data

FIGURE 8 Cross-correlation Between Steering Wheel and Lane Position Data (1 min intervals)

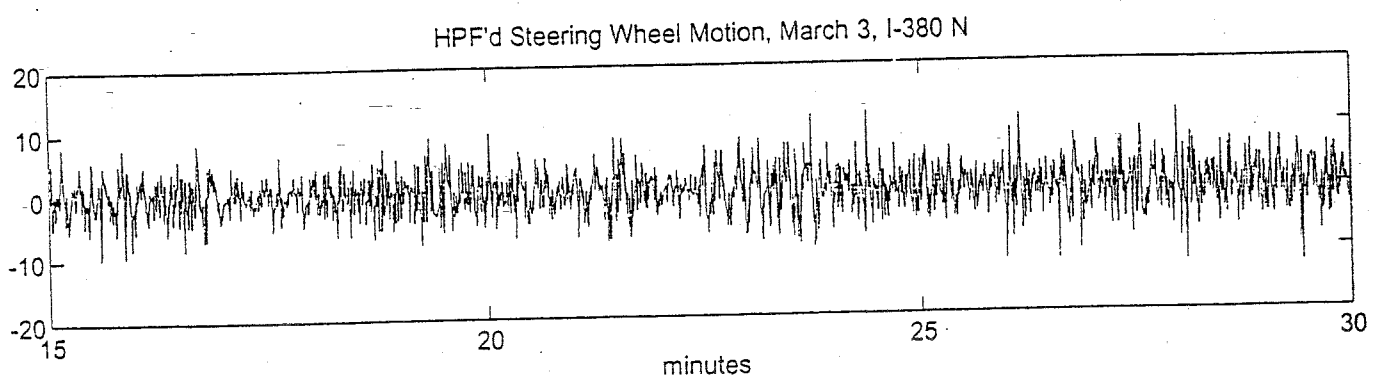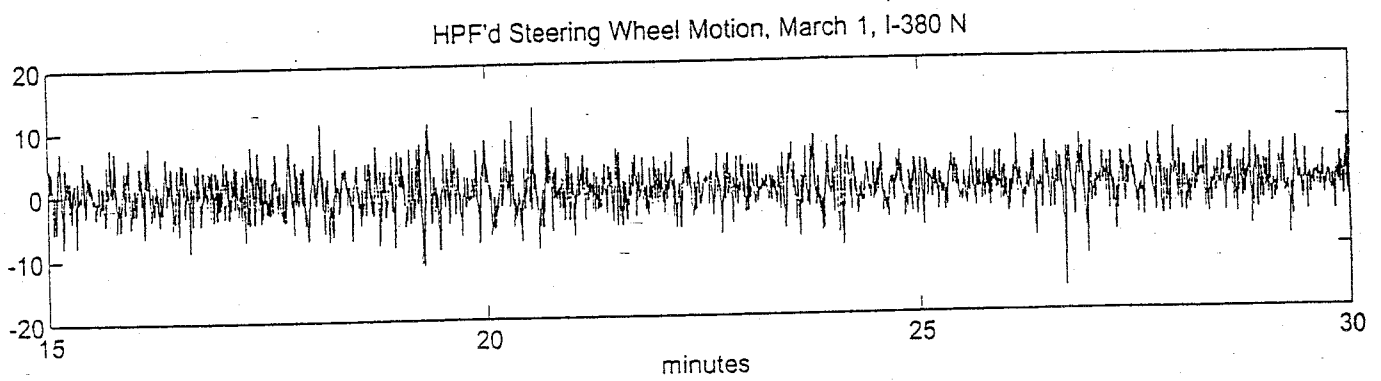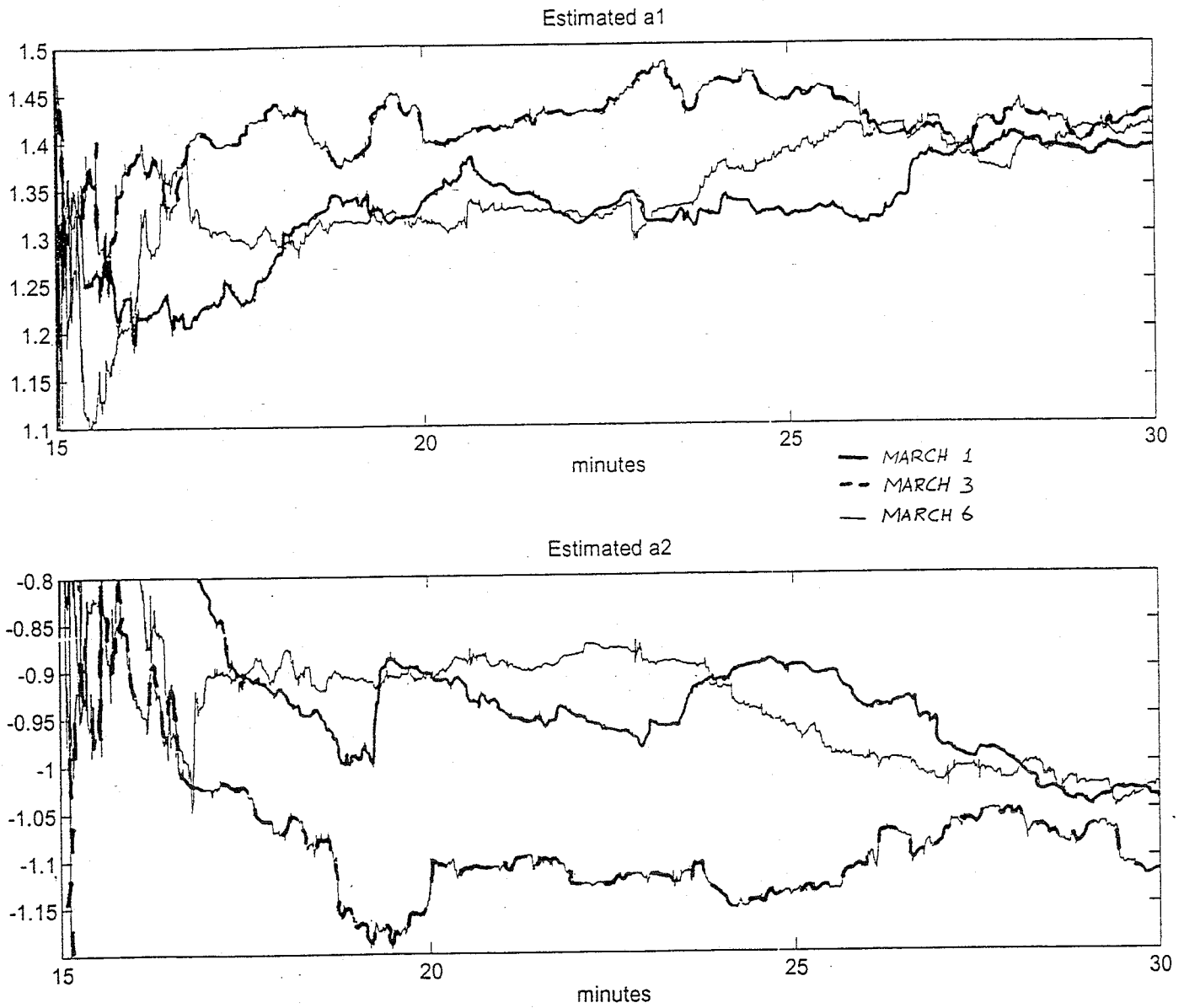Original Data (–), High Pass Filtered Data (– –), and Low Pass Filtered Data (:)
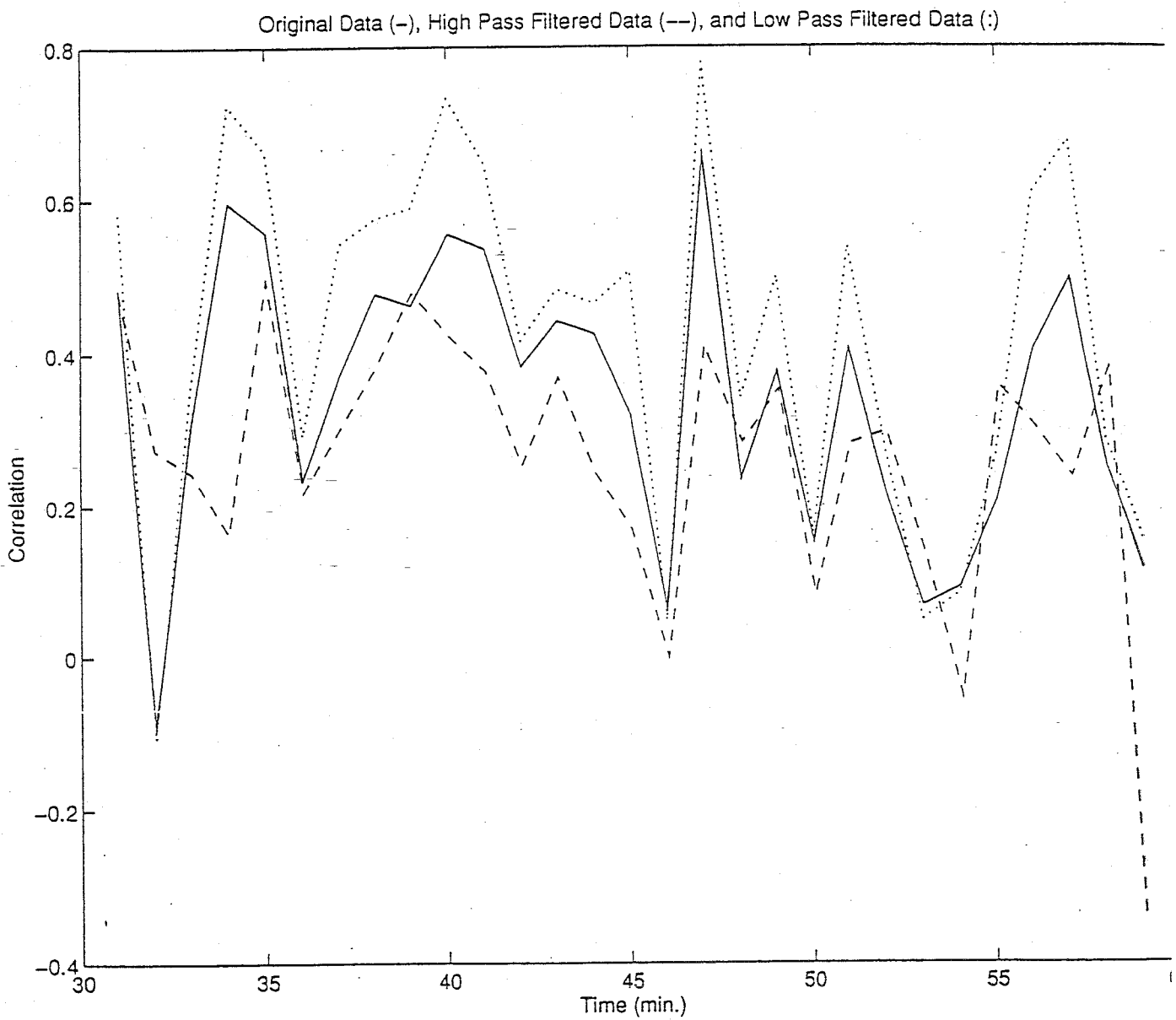
FIGURE 9 Steering Wheel Position Data for a 15 Minute Interval on I-380 for each of three days

Steering Wheel Motion, March 1, I-380 N

minutes

Steering Wheel Motion, March 3, I-380 N
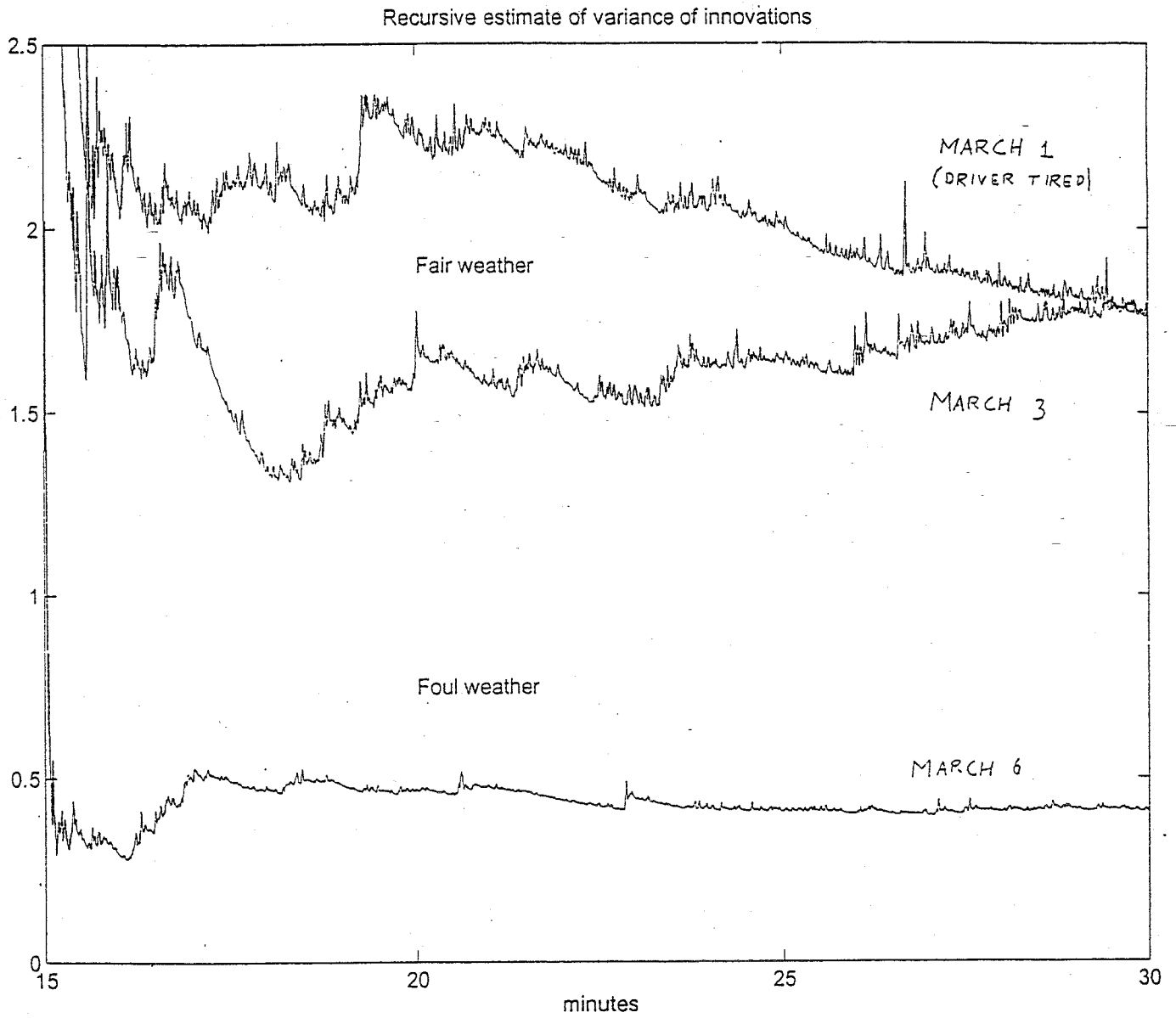
minutes

Steering Wheel Motion, March 5, I-380 N
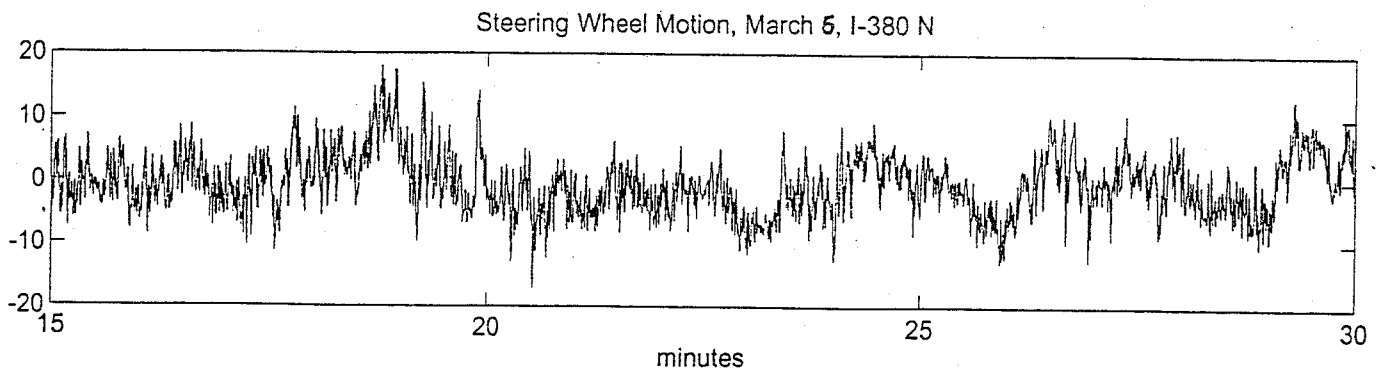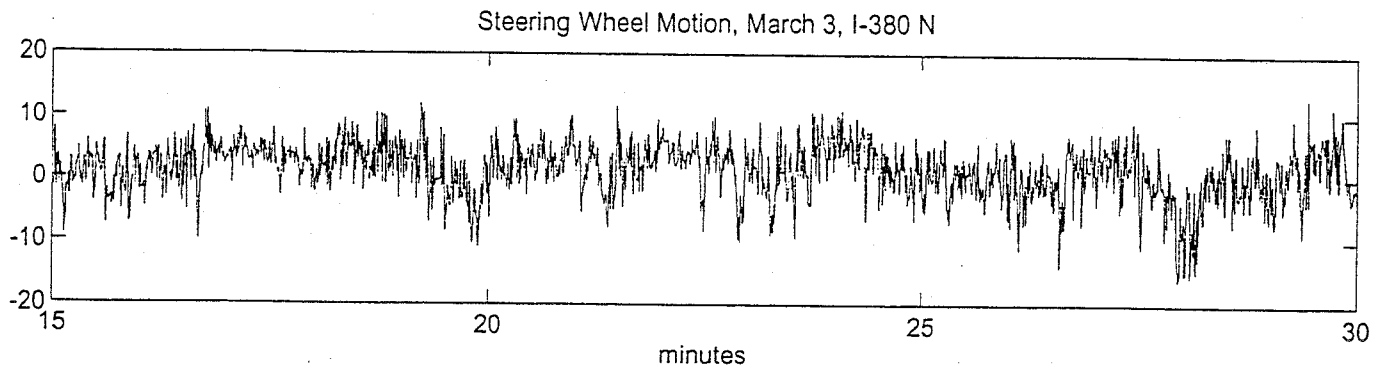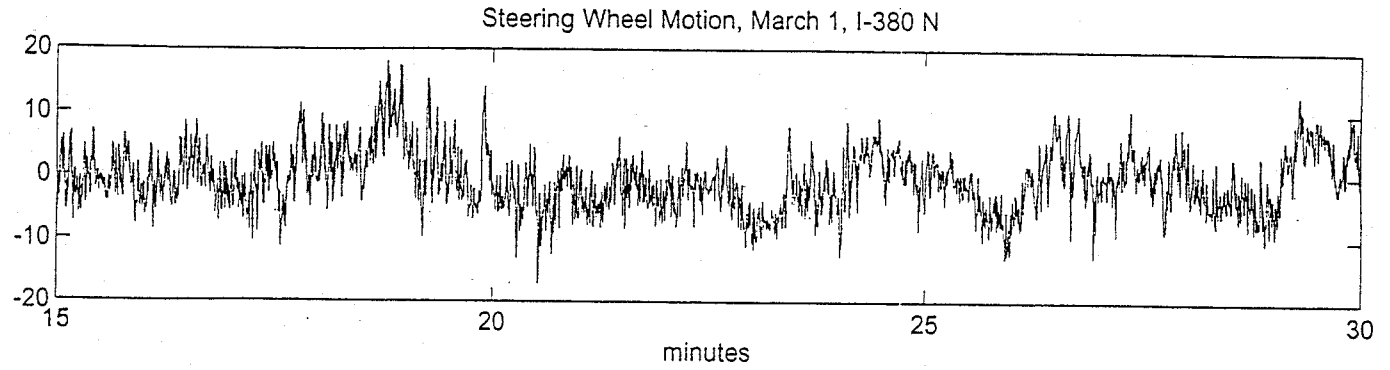
minutes

FIGURE 10 High-Pass Filtered Steering Wheel Position Data for a 15 Minute Interval on I-380 for each of Three Days

HPF'd Steering Wheel Motion, March 1, I-380 N

minutes

HPF'd Steering Wheel Motion, March 3, I-380 N

minutes

HPF'd Steering Wheel Motion, March 6, I-380 N

minutes
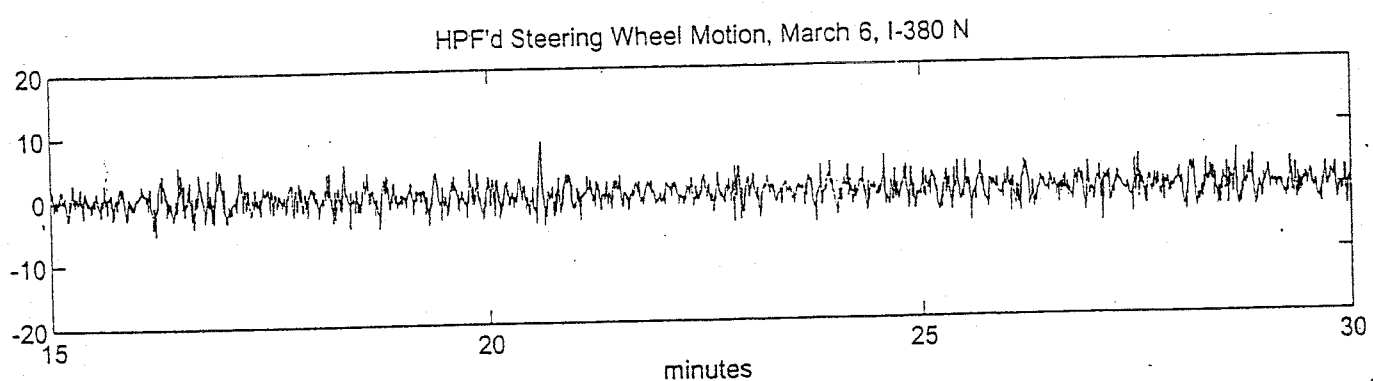
FIGURE 11 Kalman Filter Estimates of Model Parameters $\hat{a}_1$ (top) and $\hat{a}_2$(bottom) for each of Three Days
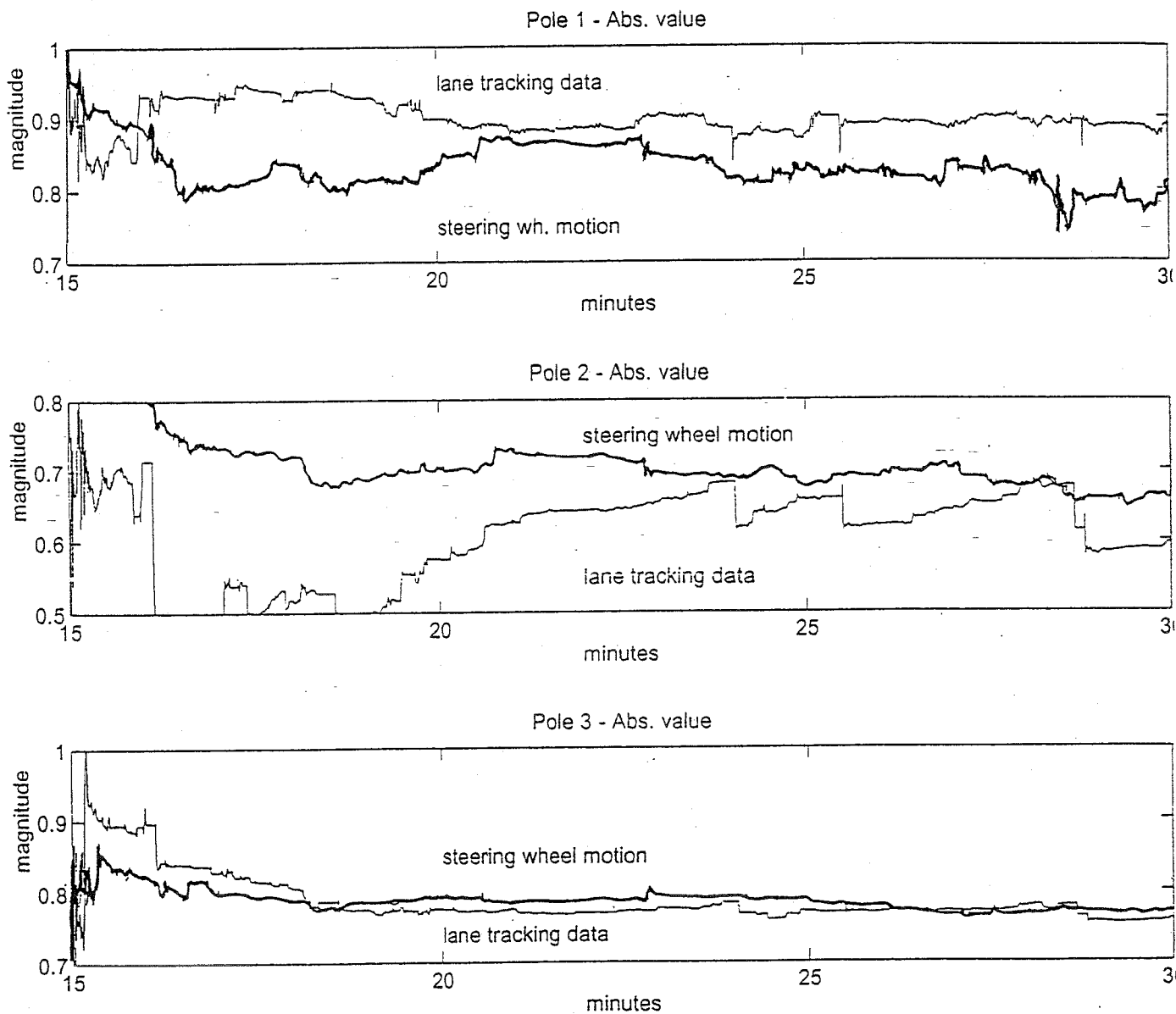

Estimated a1

Estimated a2

MARCH 1
MARCH 3
MARCH 6

FIGURE 12 Kalman Filter Estimates of the Innovations Variance for each of Three Days

Recursive estimate of variance of innovations

MARCH 1
(DRIVER TIRED)

Fair weather
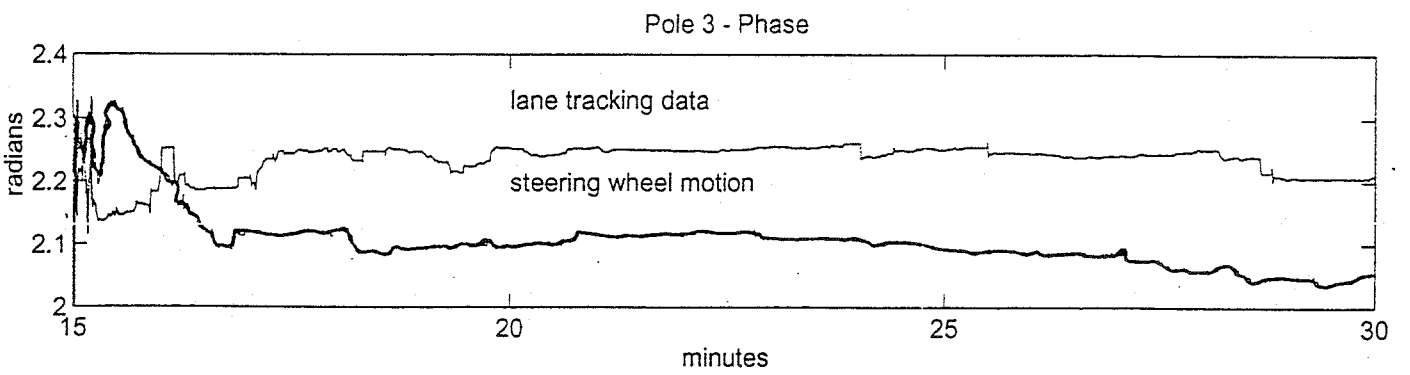
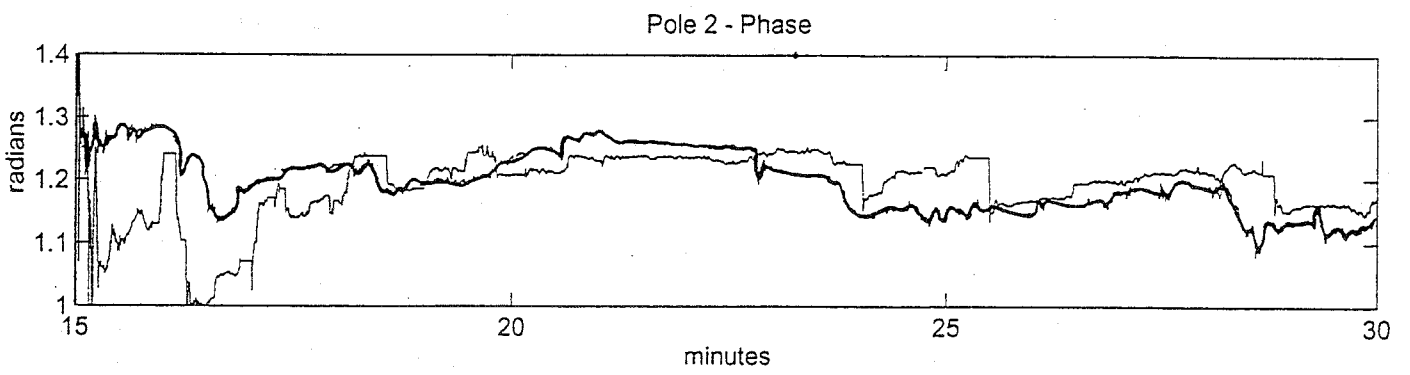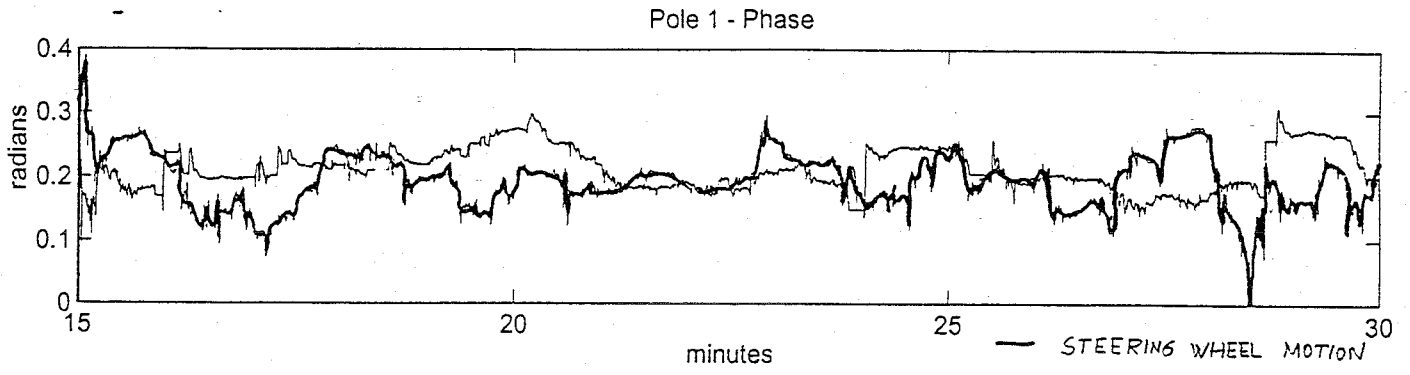MARCH 3

Foul weather

MARCH 6

minutes

FIGURE 13 High-passed Lane Position Data
Circled peaks denote regions of data collection errors. These peaks were replaced by predicted values using the Kalman filter.

Lane Tracking Data, March 6 1995
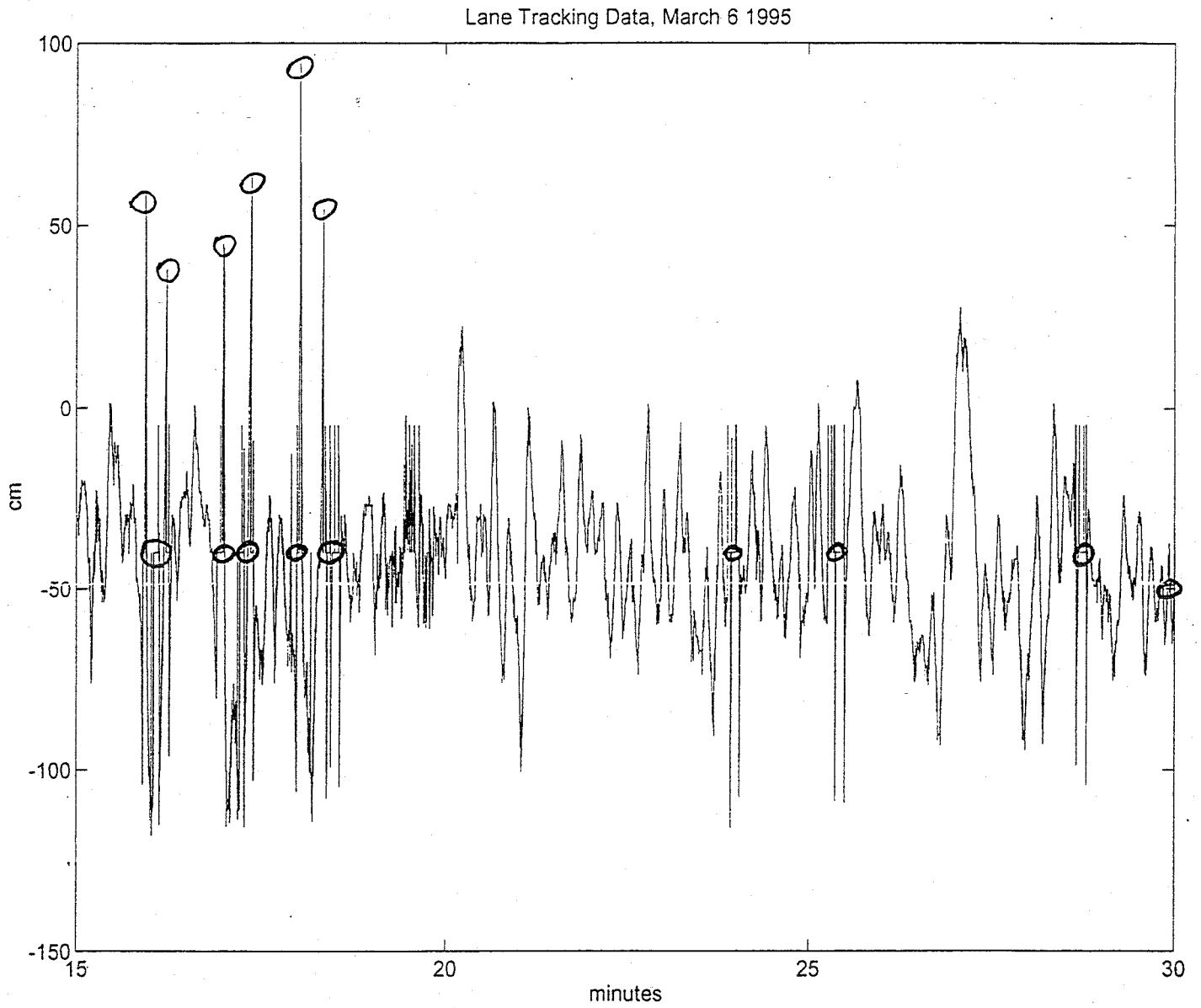
FIGURE 14 Magnitudes (top) and Phase (bottom) for each of the three complex time-varying poles associated with the Kalman-filter-based esitmates of time-varying systems related to steering wheel position (thick line) and lane position (thin line)

Pole 1 - Abs. value

Pole 2 - Abs. value

Pole 3 - Abs. value

Pole 1 - Phase

STEERING WHEEL MOTION

LANE POSITION

Pole 2 - Phase

Pole 3 - Phase

lane tracking data

steering wheel motion

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