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GENERAL MOTORS CORPORATION ■ NORTH AMERICAN OPERATIONS
RESEARCH AND DEVELOPMENT CENTER
30500 Mound Road ■ Box 9055 ■ Warren, Michigan 48090-9055

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Reported By

Zhaogang Qian
Electronic Data Systems
(810) 696-2022

Robert D. Stephens
Environmental Research Department
(810) 986-1608
8-226-1608

Approved By

Wayne France, Head
Environmental Research Department
8-226-
FAX:(810) 986-1910

Randall L. Jacobsen for
Thomas H. Caiati, Mgr. Thomas H. Caiati 3/4/94
AIS, EDS
(810) 696-2172
(810) 696-2325

Intended Audience: **ACR, GMPT, EES**

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A Decision Tree Approach To Data Validation For Remote Sensing Measurements of Vehicle Exhaust Emissions

Zhaogang Qian
Electronic Data Systems

Robert D. Stephens
GM NAO R&D Center

Abstract

The use of remote sensors to measure vehicle exhaust emissions of carbon monoxide (CO) and hydrocarbons (HC) is gaining widespread attention. Since remote sensors are capable of measuring the emissions from thousands of vehicles per day, the process of verifying the validity of the measurements must be automated. This paper presents a knowledge-based approach for solving this problem. The approach, which uses artificial intelligence with signal processing and statistical techniques, increases the accuracy and reliability of the measurements.

Supplementary Note

This report has been distributed as EV-416, dated March 3, 1994. Publication of this work will inform the technical community about the need for establishing rigorous methods to verify the validity of remote sensing measurements of vehicle exhaust emissions.

Purpose of the Research

The purpose of this research is to develop an automated process for verifying the validity of remote sensing based measurements of vehicle emissions.

Conclusions

1. The research demonstrated the effectiveness of an approach which combines Artificial Intelligence with signal processing and statistical techniques, to automate the process of validating remote sensing based measurements of vehicle emissions. Specifically, a decision tree which captures the heuristic knowledge for data validation was constructed and used in a computer program to determine the validity of the measurements. The decision tree uses several parameters about the measurements, including signal to noise ratios, synchronism and ratio of two different emissions concentrations.

2. We have shown that, for one remote sensing study, 94% of the validation task can be automated. In other words, 94% of the measurements were classified by the decision tree as either Valid or Invalid. The remaining measurements were classified by the decision tree as Uncertain, hence they need manual review for final classification as Valid or Invalid.

3. We have also shown that, without verifying the validity of the measurements, statistics about fleet emissions would be skewed, and false identification of high emitting vehicles would occur.

Significance

Through the automation of data validation, the interpretation of remote sensing based measurements of vehicle emissions has been greatly simplified, and the accuracy and reliability of the measurements has been improved. This significantly advances the transition of remote sensing from a research instrument to an I/M tool.

1 Introduction

The use of remote sensors to measure vehicle exhaust emissions of carbon monoxide (CO) and hydrocarbons (HC) is gaining widespread attention. There is the potential to use these devices to identify high emitting vehicles and thereby to improve the effectiveness of vehicle Inspection and Maintenance (I/M) programs. Also, by virtue of the ability to measure the emissions from thousands of vehicles per day, these devices offer the potential to accurately measure fleet average emissions.

Because of the tremendous number of measurements that can be obtained with this technology, it is imperative that an automated process be available for data validation. A knowledge-based approach combined with signal processing techniques and statistics was used to solve this problem with good success. In this paper, the problems inherent in validating remote sensor measurements are reviewed, as well as the knowledge-based approach taken to solve these problems.

2 Background Information

General Motors NAO Research and Development Center (GM R&DC) has designed and built a remote sensor capable of measuring the CO and HC exhaust emissions from on-road vehicles [1][1]. The GMR&DC remote sensor operates by transmitting an infrared beam across a roadway at approximately tailpipe level. Measurement of the infrared transmission through the exhaust plume of each passing vehicle provides a measure of the concentration of CO, HC, and CO_2 (carbon dioxide) in the exhaust.

The physical parameter measured by the instrument is light intensity within each of four wavelength regions; one region each for CO, CO_2, HC, and reference. The light intensity in each of the four regions is measured with no exhaust gas present (i.e. prior to the car entering the infrared beam) to provide I_o values for equation (1). After a car exits the cross-road infrared beam, light intensity in all four regions are remeasured to provide I values for equation (1).

[1] [1] describes a remote sensor with CO emission measurement capability designed by GMR&DC. HC emission measurement capability was added to the GMR&DC remote sensor at a later time.

$$T = (\frac{I}{I_o})100 \tag{1}$$

In equation (1), T is the transmittance, I is the intensity of transmitted light in the presence of a sample and I_o is the intensity of transmitted light in the absence of a sample. The remote sensor measures values of I and I_o at a rate of 200 times per second. The exhaust plume is measured for a period of approximately 0.6 seconds, hence providing approximately 110 measures of I (and T) for each channel. The T values for the CO, HC, and CO_2 channels are normalized for the T values measured on the reference channel. For example:

$$T'_{CO} = \frac{T_{CO}}{T_{REF}} \tag{2}$$

where T' is the normalized T. Normalization corrects the transmittances for light source intensity fluctuations and/or light scattering due to airborne particulate matter.

Calibration curves are generated from laboratory measurements of concentration (C) versus T. A polynomial fit of this relationship (using laboratory measurements where values of C are known) provides a mathematical relationship from which concentration can be calculated from measured values of T. For example:

$$(C)(L) = a(\%T)^1 + b(\%T)^2 + c(\%T)^3 + d(\%T)^4 + constant \tag{3}$$

In this equation, L is the distance the beam travels through the gas sample. A separate equation of this form is derived from laboratory measurements of each gas species (CO, HC, and CO_2). These equations are used to convert values of T' for CO, HC, and CO_2 to concentration-pathlength products. However, when measuring the exhaust plume of a vehicle, neither the concentration of each gas in the exhaust plume nor the pathlength of the plume is known independently (i.e. the degree of dispersion of the plume is unknown). To cancel the effect of plume dispersion, the CO/CO_2 and HC/CO_2 ratios are calculated. These ratios, which are unitless, are independent of concentration and pathlength, and hence are independent of plume dispersion. By making multiple measurements of these ratios (e.g. 110 measurements), the precision of the measurement can be determined. These ratios are then converted to tailpipe gas concentrations using equations derived from the chemistry of air/fuel combustion[2].

The accuracy of the measured CO/CO_2 and HC/CO_2 ratios are effected by a number of factors including (1) signal to noise ratio (SNR), (2) interferences from mixing of separate vehicle exhaust plumes, and (3) measurement anomalies, each of which are discussed below. For the sake of simplicity we will restrict our discussion to CO/CO_2, although the discussion applies similarly to HC/CO_2.

Measurements with low SNR can occur if the exhaust gas does not pass through or only marginally passes through the cross-road infrared beam. These situations can be described as a plume miss or near plume miss, respectively. Under these conditions it is possible to have modestly high CO/CO_2 ratios while simultaneously having CO and/or CO_2 values below the detection limit of the instrument, i.e. low SNR. SNR is also adversely effected by rapid plume dispersion. Near plume misses represent the most difficult measurements to verify, and also represent the most frequent type of measurement problem.

A plume interference can occur if the exhaust of one vehicle is present when another vehicle with different exhaust concentrations of CO and CO_2 passes the remote sensor. A measurement under such conditions would result in an erroneous CO/CO_2 ratio. This is because the CO/CO_2 ratio would not remain constant as the two plumes are mixing.

Measurement anomalies can occur due to repetitive blockage or partial blockage of the infrared beam by portions of a car or a trailer. Occasionally when this occurs, the normalization process (equation 2) does not accurately correct the measured transmittance. This is because the infrared detectors cannot be perfectly aligned relative to each other, i.e. each detector has a slightly different field of view.

An example of a typical exhaust plume measurement by the GMR&DC remote sensor is shown in Figures 1a through 1c, where CO_2 levels are detected at reasonable levels and CO and HC levels are quite low. Such a measurement is typical because the majority of vehicles emit very low levels of CO and HC. Figures 1d-f show the same data after applying a digital filter to reduce noise levels (as discussed in section 4). Figures 2a through 2c show CO, CO_2, and HC versus time data for the measurement of a high CO and HC emitter (after digital filtering). The concentrations plotted in these figures are values relative to a 4 inch pathlength (L). To determine the CO/CO_2 ratio, the CO concentrations are plotted as a function of the CO_2 concentration. The slope of this relationship (determined by regression analysis) is the CO/CO_2 ratio. An analogous calculation is done for HC/CO_2.

Examples of some of the potential measurement problems are shown in Figures 2d through 2f and 3a through 3c. Figures 2d through 2f show an example of a plume miss, i.e. CO, HC, and CO_2 levels are near zero during the measurement. In this plot, the variation in concentration as a function of time is largely the result of instrument noise. Sometimes, such noise can be highly correlated and results in erroneously high CO/CO_2 and HC/CO_2 ratios. Figures 3a through 3c show an example of a partial mechanical beam blockage that gives rise to a sudden shift in measured concentrations.

Each of the problems displayed occur in a small fraction of total vehicle measurements. Many of these problems result in very high values of CO/CO_2. Since the frequency of high emitting vehicles is very low, a small percentage of erroneously high emissions readings could result in a large error in this frequency. In the following discussion, we will review one approach to identifying and correcting these problems.

3 Decision Tree: A Knowledge-based Approach

Some of the inherent problems in data validation make it difficult to automate the process by a traditional approach. There are no existing mathematical models or clear-cut, quantitative criteria for validating the measurements. Validating a measurement requires that a judgement be made which is based upon an understanding of the principles of the instrument and experience with instrument performance.

Nevertheless, these problems are exactly the ones that artificial intelligence tries to tackle. Because heuristic knowledge plays a key role in validating the measurements, a knowledge-based solution is most appropriate for this application. For instance, from the discussion in the previous section, we know that if both CO SNR and CO_2 SNR are low, the measurement is a plume miss or near plume miss, and hence is invalid. Another example of an invalid measurement occurs when both CO SNR and CO_2 SNR are high, but the signals of CO and CO_2 are not synchronized. If the knowledge to identify these problems can be captured and stored in a knowledge base, validation can be automated. A knowledge-based approach was adopted to solve these data validation problems.

To capture the knowledge required to validate the measurements, we need a knowledge representation scheme which best suits the needs of the application. In this application, we use a decision tree as a tool to represent the domain knowledge. A decision tree is a tree-like structure with a parameter name associated with each non-leaf node of the tree, a parameter value associated with each branch of the tree, and a class name associated with each leaf node. In a decision tree, each path from the root node to a leaf node represents a classification rule. For this application, a decision tree approach is well justified because data validation is essentially a classification problem that requires very little reasoning. Furthermore, a decision tree is not only simple to implement, but is also very efficient.

To construct a decision tree for this task, three steps were taken: (1) a list of parameters which characterize a measurement were defined, (2) the structure of the decision tree was defined, i.e., the order in which the parameters are tested was assigned and (3) the parameter value at each branch was determined.

The parameters for the decision tree must quantitatively characterize the signals in a measurement. We defined several parameters including signal to noise ratio (SNR), minimal detectable limit (MDL), synchronism (SYN), ratio of two concentrations (Slope), and standard deviation of the ratio (STD). Various techniques are used to define these parameters. In particular, a signal processing technique is used to derive SNR; statistics are used to calculate Slope and STD; some hueristics borrowed from pattern recognition is used to define SYN; and a hypothesis test is used to estimate MDL.

To accomplish (2) and (3), two approaches can be taken. One is to automatically generate the decision tree from examples using ID3 or ID3-like machine learning techniques [3, 4]. The other is to hand craft the decision tree through knowledge acquisition. We first experimented with the machine learning approach. By manually classifying a set of sample measurements as "valid high emitter", "valid low emitter", "invalid due to low SNR", "invalid due to low synchronism", and feeding the sample measurements into a machine learning program, we generated a decision tree. Although the machine learning program generated a fairly correct decision tree for measurements whose parameter values were not on the borderlines, automatic generation of a decision tree covering all cases was extremely difficult. To derive a useable decision tree, we adopted the second approach. A good decision tree was constructed by interpreting the human judgements in validating the data as well as by trial and error.

In what follows, we discuss the knowledge that is used for data validation, in terms of the parameter definitions and branching value determinations.

3.1 Computing Signal To Noise Ratio

For a measurement to be valid it must have a high SNR. At low SNR, the CO, CO_2, and HC concentrations are undetectable, or effected by instrument noise to the extent that the calculated CO/CO_2 and HC/CO_2 ratios are erroneous. Therefore, to validate the measurements, an effective way to compute the SNR is essential. From Figures 1a-c it can be observed that the noise frequencies are high relative to the signal frequencies, therefore, a low pass filter can be employed to separate signal from noise frequencies. The filter serves two purposes: (1) it removes high frequency noise from the raw signal so that the CO/CO_2 ratio is more accurate, and (2) it separates the signal and noise so that SNR can be calculated. Our software uses a nonrecursive filter based upon the Fourier design with a Hamming type window [5].

The ability of the low pass filter to extract signal from noise is shown in Figures 1d, 1e, and 1f. We verified that the filter does not adversely effect the signals by plotting filtered versus unfiltered CO/CO_2, as shown in Figure 4a. The benefit of the filter is shown in Figure 4b, which plots the relative standard deviation of the ratio calculated after filtering versus before filtering for each of several thousand experimental measurements. A regression analysis of these data indicate that the filtering decreases the standard deviation of the measurements by approximately 66%. Without filtering, the statistical uncertainty of many of these measurements was too large for the measurement to be meaningful.

The filter also provides a means of calculating SNR. The signal energy and the noise energy are computed according to the following equations:

$$E_s = \sum_{i=1}^{n} y_i^2 \tag{4}$$

$$E_n = \sum_{i=1}^{n}(x_i - y_i)^2 \tag{5}$$

where x_i is the ith sample of the digital signal, y_i is the ith output of the filter, and n is the number of samples in the digital signal.

Using the signal and noise values calculated as above, the SNR can be determined as follows:

$$SNR = \sqrt{\frac{E_s}{E_n}} \tag{6}$$

The vast majority of vehicles in operation (more than 99%) have exhaust CO/CO_2 ratios of less than one. Indeed, most vehicles emit less than 1% CO (i.e. $CO/CO_2 \leq 0.07$). Hence, most measurements suffer from having a low CO SNR. This is particularly true for near plume miss measurements, i.e. measurements that have a low CO_2 SNR. As the CO_2 SNR decreases, CO can only be detected at a higher CO/CO_2 ratio. To identify such cases, we calculate the minimum detectable level (MDL) of CO/CO_2. If the MDL is above an arbitrary minimum, the uncertainty in CO/CO_2 is unacceptably high and the measurement is invalid. Cases of high MDL and/or low CO_2 SNR are considered plume miss errors. We require that all measurements have a measured CO_2 SNR greater than 3.0 to be valid, otherwise the measurement is considered a plume miss error. Also, cases of high CO/CO_2 with CO SNR of less than 2.0 are plume misses. Of 30,914 recent measurements, 12.5% were found to be plume miss errors.

3.2 Plume Interference Detection

To confirm that CO, CO_2, and HC have a common source, a test of the standard deviation of CO/CO_2 is used. All measurements must have a standard deviation of the CO/CO_2 ratio of less than either 0.07 or 10% of the ratio (whichever value is larger). For measurements with a high CO/CO_2, i.e. greater than 0.07, additional tests are applied. For such high ratios to be valid, the CO and CO_2 signals must both have high SNR and the signals must be synchronized with each other. If they are not synchronized, a secondary source of CO or CO_2 is present, or a problem is present with the measurement and it should be considered invalid. To test the synchronism, a parameter we will call the estimated CO_2 signal is calculated:

$$y'_{CO_{2_i}} = \frac{y_{CO_i} - b}{a} \tag{7}$$

where y_{CO_i} is the filtered CO signal, a is the CO/CO_2 ratio, and b is the intercept obtained from the regressions analysis of CO versus CO_2. Hence, the estimated CO_2 signal is the CO signal scaled by the reciprocal of the measured CO/CO_2 ratio. The estimated CO_2 signal is compared, point by point, to the filtered CO_2 signal to yield a parameter we call Synchronism (SYN):

$$SYN = \sqrt{\frac{\sum_{i=1}^{n}(y'_{CO_{2_i}} - y_{CO_{2_i}})^2}{n}} \tag{8}$$

SYN gives the averaged point to point difference between the estimated CO_2 signal and the filtered CO_2 signal. A small value of SYN indicates that the CO and CO_2 signals are synchronized. This SYN term is used along with the standard deviation of the CO/CO_2 as a means of determining a plume interference error.

Approximately 6% of measurements were found to have plume interference errors due either to SYN or standard deviation. Previous studies have indicated that the frequency of this interference increases with traffic density [6, 1].

3.3 Data Anomalies

Measurement anomalies are another source of invalid measurements. Two types of anomalies often observed in the GM instrument are: (1) the presence of concentration spikes in the CO, CO_2, and/or HC signal and (2) a step function change in concentrations of CO, CO_2, and/or HC as is shown in Figures 3a-c. These phenomena occur most typically when the infrared beam is partially blocked by mechanical objects attached to, or being pulled by the vehicle being measured. Examples include vehicle bumpers, trailer hitches, low hanging mufflers, and/or trailers.

To eliminate the spikes in the CO, CO_2, and HC signals, a clustering algorithm is used to detect the spikes. In the clustering algorithm, a data point is considered a spike if its "local median distance", i.e. the absolute difference between a point, x, and the median of all points within a window of points surrounding x, is greater than a certain threshold. Once a data point is identified as a spike, it is replaced by the average value of a given number of neighboring points.

The step function is identified by a simple digital filter. The digital filter is defined as follows:

$$y_i = x_{i-l} - x_{i+l} \qquad i = 1...n \tag{9}$$

where l is the length of the filter. To identify the step function, a threshold and the filter length must be chosen. If there is a y_i whose absolute value is greater than the chosen threshold, then the digital signal is a step function. Step functions have been identified in approximately 1.4% of measurements.

4 Discussion

Remote sensors are capable of making thousands of vehicle measurements per day, hence, the technique provides the capability of determining the average emissions from large fleets of on-road vehicles. The technique also has the potential to be used in vehicle Inspection and Maintenance programs as a means to identify vehicles that have high emissions and therefore are in need of repair. Since the technique performs high volumes of measurements, it is crucial that an automated process be available to distinguish between valid and invalid measurements. This automated process must be reliable so that remote sensors do not misidentify vehicles as high emitters. Prototype software, utilizing the previously described decision tree approach, has been implemented and tested on 30,914 remote sensing measurements [7]. Using this data, we have evaluated the effectiveness of this validation process and subsequently determined the impact of the validation process on the measured emissions of CO from this fleet of vehicles. We have also determined the impact of the validation process on the frequency of high emitters (i.e. CO greater than 4%).

The software sorts measurements into three classes: Valid, Invalid and Uncertain. Measurements in the Uncertain category require manual review for final classification as Valid and Invalid. Table 1 shows the number of measurements within each of these classifications, as well as the mean and median %CO, and the number of high emitters in each classification. From

Table 1: Statistics for each class of data

	Number of measure.	Mean %CO	Median %CO	Number of high emitters	High emitter frequency[2]
Invalid	6,281	-1.46	0.46	766	12.2
Uncertain	1,869	4.64	0.47	473	25.3
Manual Invalid	866	6.76	0.24	179	20.7
Manual Valid	1,003	2.81	0.66	294	29.3
Valid	22,764	0.68	0.14	1,121	4.9
Total Invalid	7,147	-0.47	0.43	945	13.2
Total Valid	23,767	0.77	0.15	1,415	5.9
Total	30,914	0.48	0.18	2,360	7.6

this data, we have determined that 94% of all measurements can be classified by the software as Valid or Invalid, hence eliminating the need for manual review of most of the measurements.

We have evaluated the impact of this classification process on the measured fleet average emissions of CO. Table 1 illustrates that the overall mean emissions vary according to data classification. For example, the outcome of the combined manual and automated classification process indicates that Valid measurements have a mean CO of 0.77%. If no classification were performed, the mean emissions would have been reported as 0.48% CO. A student's t-test of these means indicate that these values are unequal at the 95th percentile confidence level. Hence, we conclude that the validation process is required to accurately measure the average emissions of on-road vehicles.

We have also investigated the importance of the manual review of the data in the Uncertain classification, by testing the significance of the difference in means of the Valid and the Total Valid categories. A student's t-test finds that, at the 95th percentile confidence level, these means are different. This suggests that measurements in the Uncertain category must be manually reviewed to accurately measure fleet average emissions. Hence, the Uncertain class of measurements cannot be disregarded.

[2] High emitter frequency = (Number of high emitters / Number of measurements) * 100.

The data in Table 1 also suggests that, in the absence of a validation process, the number of high emitters in the fleet would be overestimated. Also, the number of high emitters in the Uncertain class is higher than is present in either the Valid or Invalid class. Hence, without manual review of the Uncertain class, the number of high emitters would be underestimated.

5 Recommendations

To further improve the effectiveness of automated data validation, two directions of investigation must be pursued. One is to reduce the number of measurements in the Uncertain category, so that a higher percentage of data validation can be automated. The other is to reduce the percentage of visual invalid in the Uncertain category. If this percentage is low enough, the total automation of data validation can be achieved by merging the Uncertain category with the Valid category.

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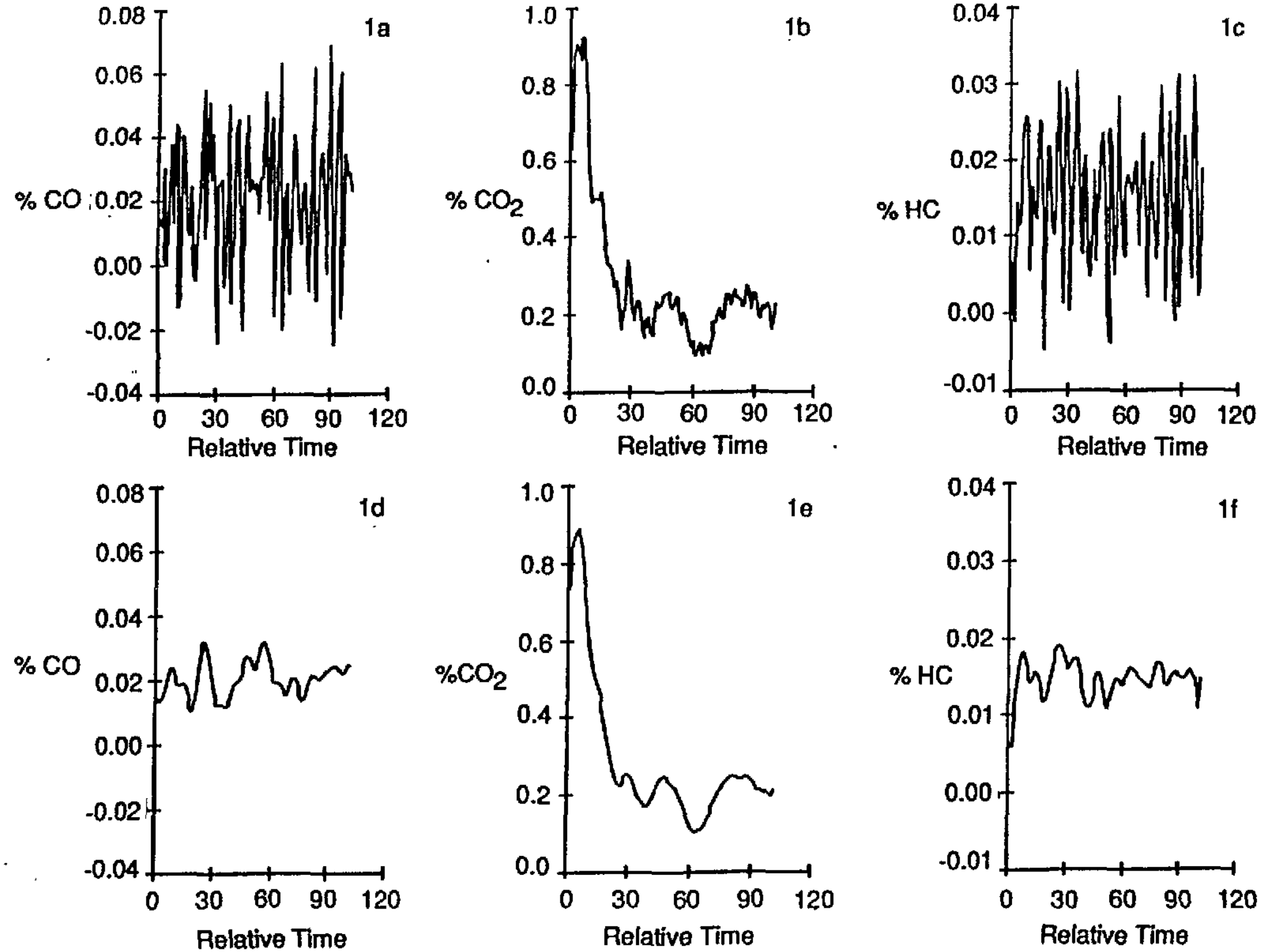

Figure 1. These plots show the concentration as a function of time for (a) CO (b) CO_2 and (c) HC as measured for a *typical* vehicle emitting less than 1% CO by volume in the exhaust. The same data after applying a digital filter for noise reduction (as discussed in Section 4) is shown in (d), (e), and (f).

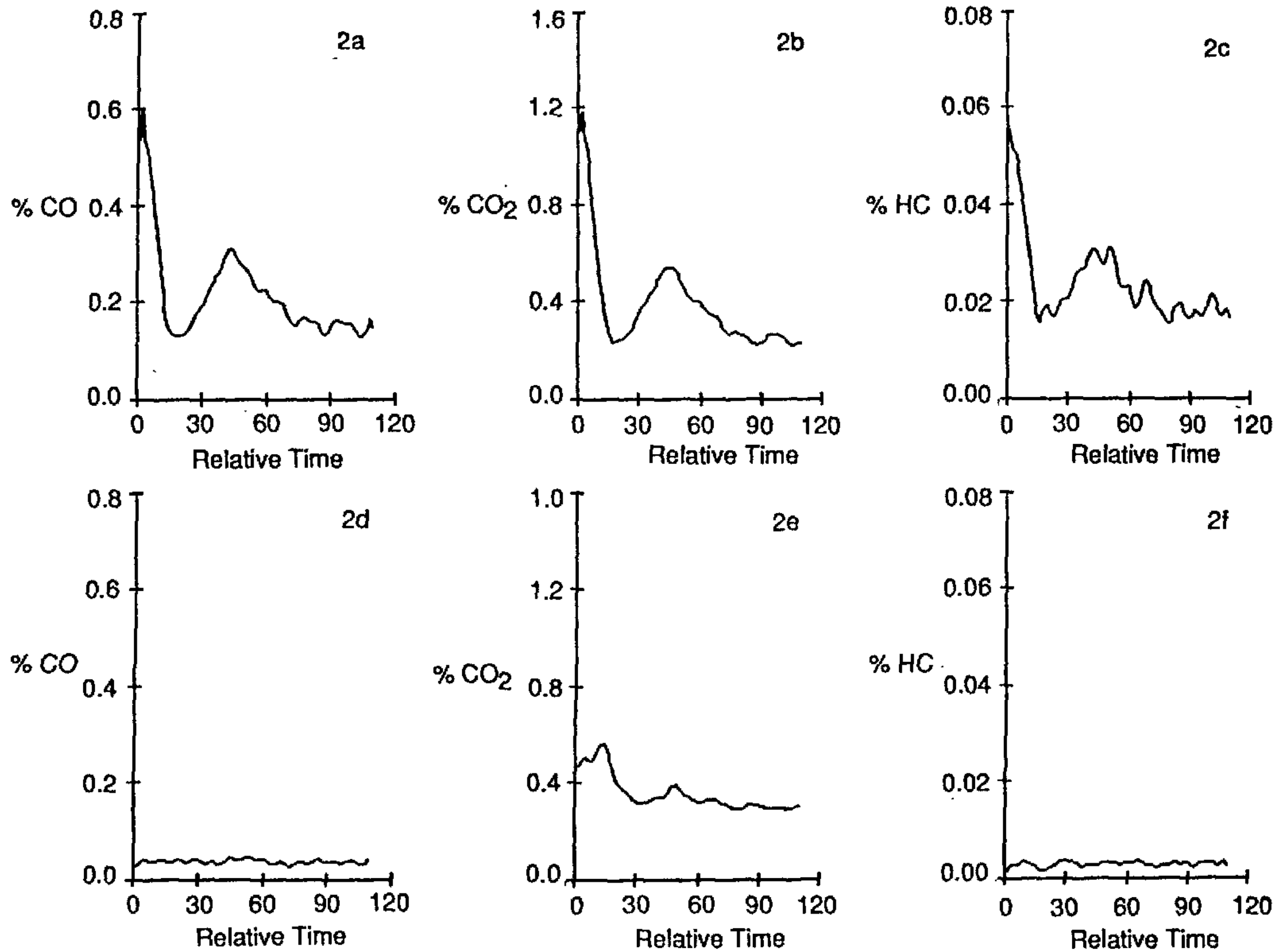

Figure 2. These plots show the concentration as a function of time for a) CO, b) CO_2 and c) HC as measured for a high emitting vehicle (5.3% CO and 0.48% HC by *volume in the exhaust). Equivalent data is shown in d, e, and f for a plume miss.*

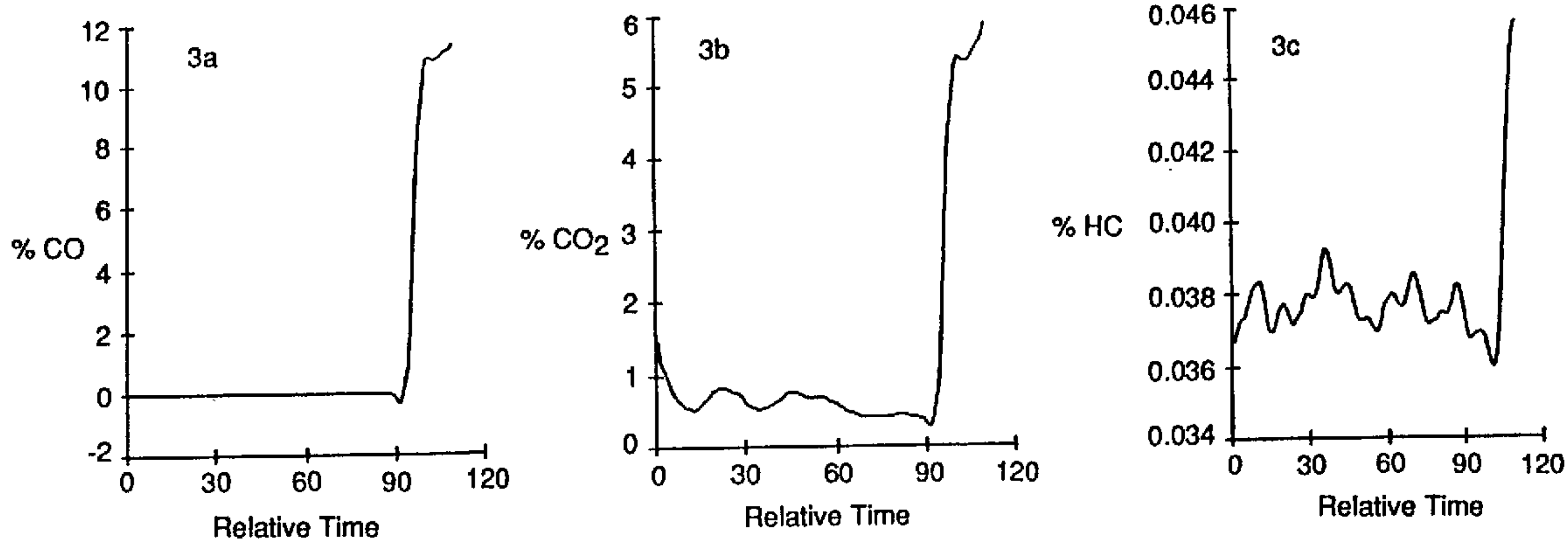

Figure 3. Concentration versus time data is shown for a) CO and b) CO_2 and c) HC. The sharp rise in concentration at relative time = 91 is an anomaly due to partial blockage of the infrared beam.

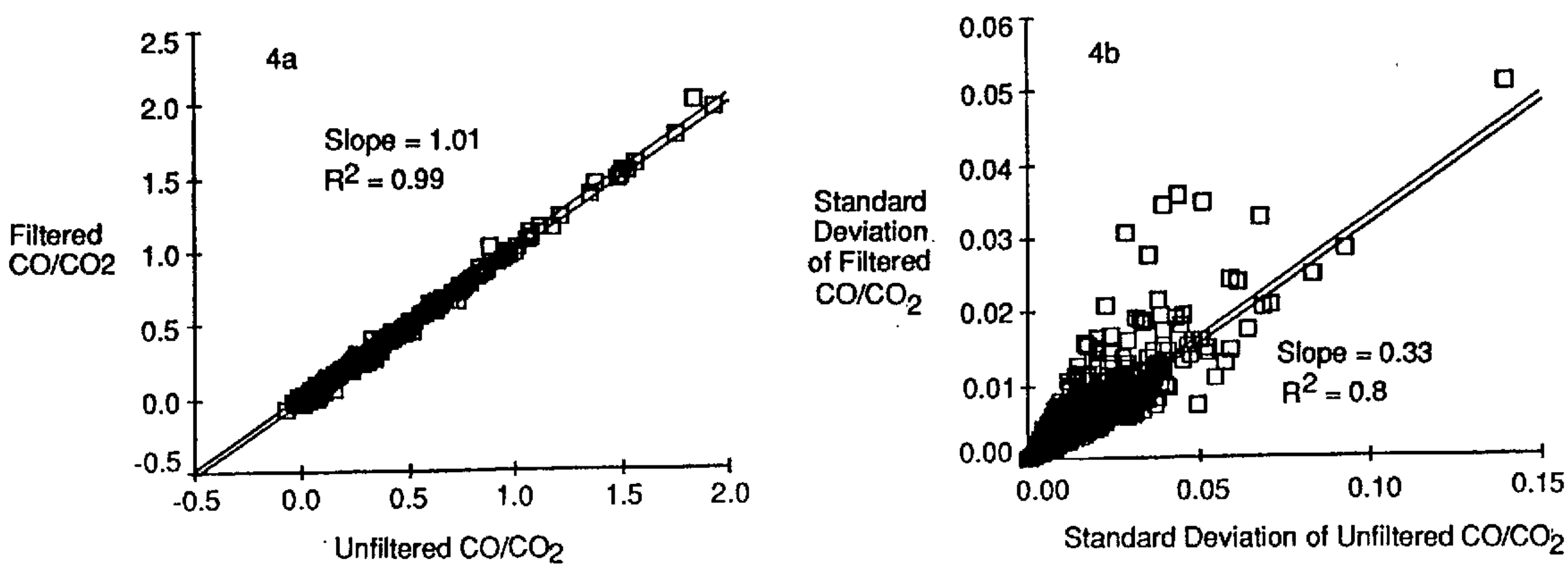

Figure 4. These plots show the effect of the digital filter on a) measured CO/CO_2 and b) the standard deviation of CO/CO_2.

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