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STATISTICAL METHODS FOR PASSIVE VEHICLE CLASSIFICATION IN URBAN TRAFFIC SURVEILLANCE AND CONTROL

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16. Abstract
A statistical approach to passive vehicle classification using the phase-shift signature from electromagnetic presence-type vehicle detectors is developed with digitized samples of the analog phase-shift signature, the problem of classifying vehicle type is formulated as a problem in classical maximum likelihood hypothesis testing. Computer algorithms for performing classification are developed and evaluated using data from ten different vehicle types. Simulation of the algorithms using these data has shown very favorable detection performance over a wide range of signal-to-noise ratio with high detection probabilities and low frequency of misclassification. A methodology for algorithm simplification and calibration is proposed which may permit implementation on simple (e.g., microprocessor based) signal-processing hardware.

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PREFACE

This research was performed under the U.S. Department of Transportation, Research and Special Projects Administration, Contract No. DOT/TSC-1456, to "Investigate Control Strategies for Urban Grid Networks". The author gratefully acknowledges the computational programming assistance provided by Paul J. Sylvester of M.I.T., and the criticism and support of Diarmuid O'Mathuna of the Transportation Systems Center.

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1. INTRODUCTION

1.1 Problem

This report describes a technique for vehicle classification or identification using the electromagnetic signature from presence-type vehicle detectors. Vehicle classification is increasingly likely to be an important component of real-time urban traffic management by digital computer. Typical applications where vehicle classification is important currently include bus prioritized freeway access and traffic signal pre-emption on surface streets. As more sophisticated public transit control strategies are contemplated, such as headway maintenance for public transit on surface streets, location information also plays a key role. For general traffic flow surveillance data processing, classification of vehicle type permits more accurate estimates of its length and hence speed using single detector arrangements [3].

Our goal in this study is to restrict attention to vehicle identification which: (i) is vehicle-passive i.e., requires no apparatus or devices on board the vehicle to function; (ii) can operate using data from conventional "presence-type instruments (e.g., resonant loops and magnetic gradient detectors); (iii) can be applied to a reasonable spectrum of vehicle types, spanning private auto and public transit vehicles; and (iv) can be implemented on simple digital signal-processing devices, such as those based on microcomputers. Our results provide a statistical formulation of the vehicle classification problem using a time-discrete sampled version of loop detector phase shift and classical hypothesis testing techniques.

1.2 Background

The basic idea employed in our approach is not new. It relies on the fact that as vehicles such as a bus, truck or car pass over a conventional presence-type detector, an electronic signal (e.g., the phase shift between the voltage and current in the detector loop) can be observed which varies among different vehicle types. It has been shown that such signals possess certain features characteristic of the vehicle type, collectively denoted as studies of the impact of certain aspects such as detector-loop geometry to enhance vehicle-signature features may be possible, and initial studies tend to discourage optimism for significant improvements following this approach [2]. Moreover, from a cost-benefit perspective, it is desirable that the classification technology be applicable to the large number of existing detector loops. Therefore, we do not consider these detector hardware-design aspects here.

1.3 Approach and Organization of Report

Our approach to passive vehicle classification uses a digitally sampled version of the analog-detector signature. A statistical model for the various signatures and their sampled versions is developed in Section 2. Then in Section 3, we show how the vehicle classification problem can be formulated as one in elementary statistical hypothesis-testing, based on the signature models. What results is a computational algorithm based on elementary likelihood ratio calculations. Computational implementation of these tests in the context of the vehicle-classification problem are addressed in Section 4, including modeling approximations, required sample-size (computer-storage) requirements, and simplifications of the tests that result in a number of special cases of interest. We examine the performance of the classification method in a simulation based on phase-shift signatures obtained for 10 different vehicle types in reference [2]. These tests include two types of buses, two types of passenger cars, five different trucks, and one motorcycle. In each case, it is shown that the algorithm developed here provides high frequency of correct classification with relatively low frequency of incorrect classification (or cross detections) over a wide range of signal-to-noise ratio. Finally in Section 5, we provide some suggestions for further study relating to performance improvement and implementation of the methods developed.

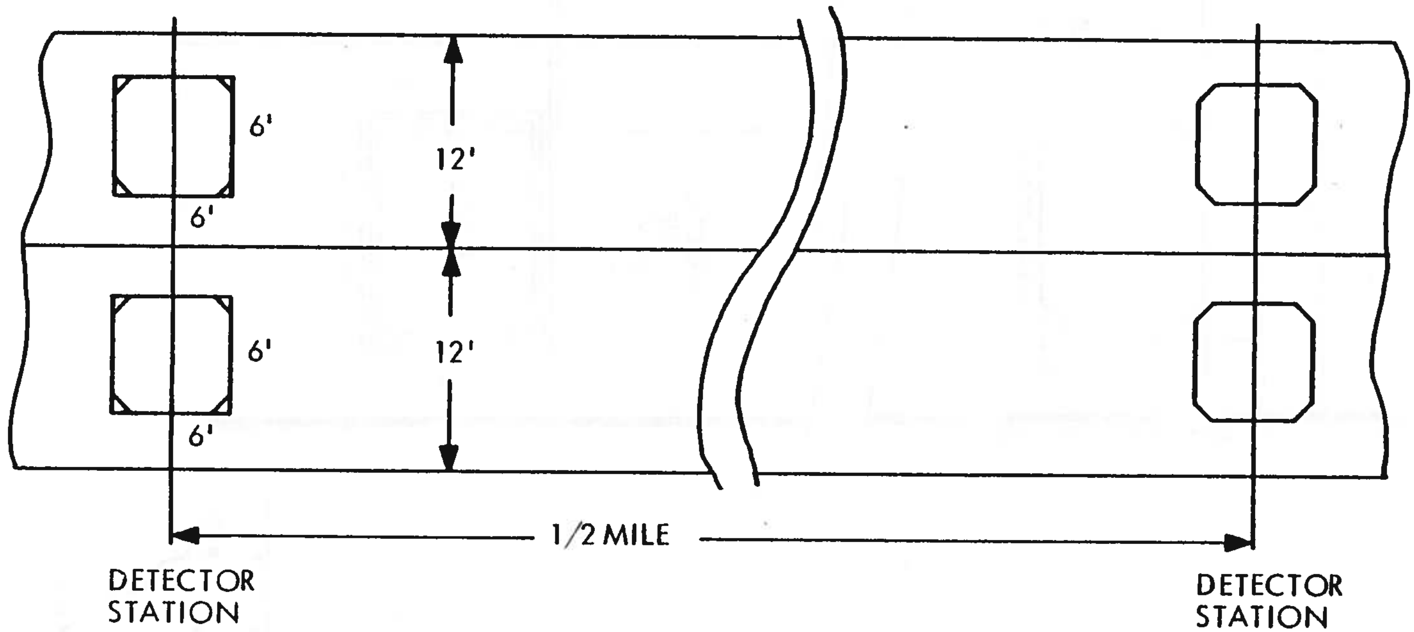

Figure 2.1: Typical Presence Detector Configuration on Freeway

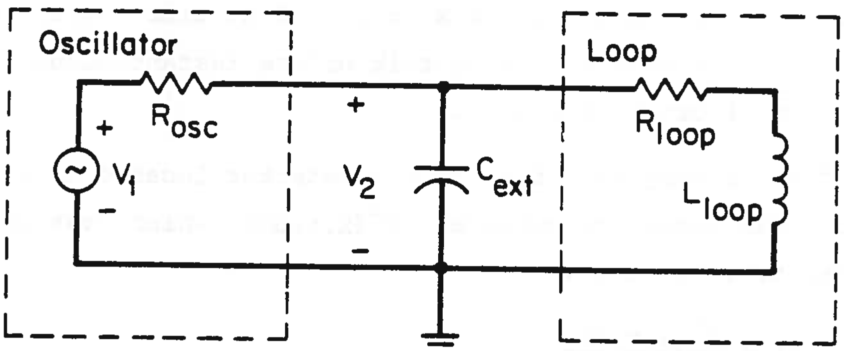

Figure 2.3 (a): Loop Detector

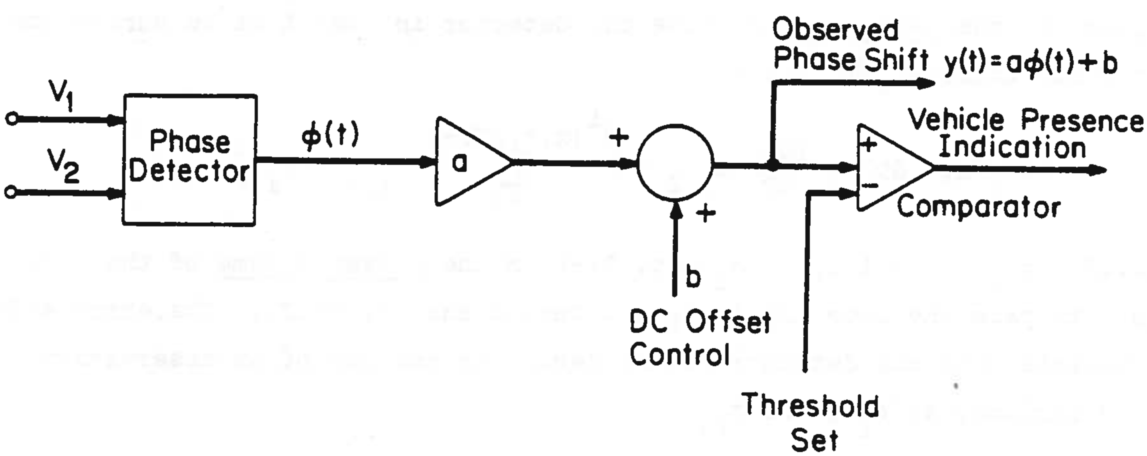

Figure 2.3 (b): Loop-Detector Electronics

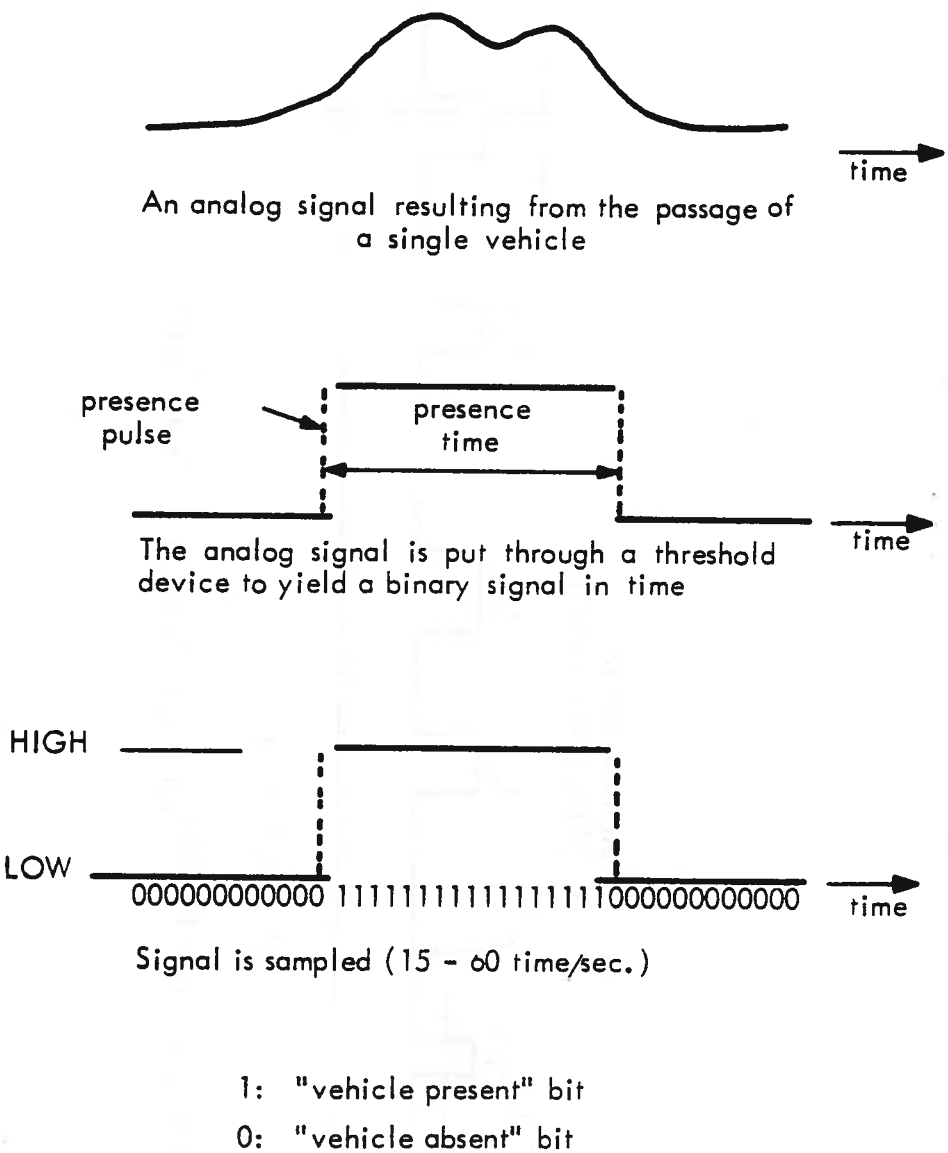

Figure 2.4: Presence-Detector Signals Associated with Single-Vehicle Passage

density flows, or where short observation intervals, ΔT, result in $M^i(x;t,\Delta T)$ being "small". In general, traffic-surveillance work compensation for the effects of such errors can be provided by a Kalman filter algorithm (see; e.g., [3]).

Intuitively at least, the quantity occupancy is proportional to density. At higher density, one expects to see a vehicle over a detector a greater percentage of the time and conversely. However, a precise model for this intuitive relationship must be developed with care because occupancy is a time-average quantity at a point, whereas density is a spatially defined quantity, at a given time. Conditions under which one can be derived approximately from the other are obtained in Kurkjian [4].

2.3 Analog-Detector Data as Vehicle Signature

A closer examination of the analog electronic signals in a detector reveals that information is present which is normally removed in the process of flow and occupancy quantization. Of particular interest is the analog-phase shift as defined in Section 2.1. As a function of vehicle position over the detector loop, different detector technologies result in different phase-shift responses. For example, a conventional loop-detector phase response is compared with the so-called magnetic gradient vehicle detector (see discussion in reference [1]) in Figure 2.6. Whatever technology is employed, an even more careful examination of the phase-response waveforms reveals a collection of more subtle characteristic "bumps and wiggles", or signature, which can often be uniquely associated with specific vehicle types. For example, in Figure 2.7 we compare phase-shift signatures from reference [2] for conventional loop detectors for two passenger vehicles (Volkswagen Sedan and Ford Torino) with two buses (GMC and Flxible buses of comparable size), in which variations due to both vehicle length and vehicle speed have been normalized out (see below)*. In these normalized coordinates, the key features are seen to be qualitative variations in the amplitude of the phase shift. Note for example that the different passenger-vehicle types have one

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* Ten different vehicle types have been used in this study (from reference [2]), and are included in Appendix A and discussed further in Section 4.

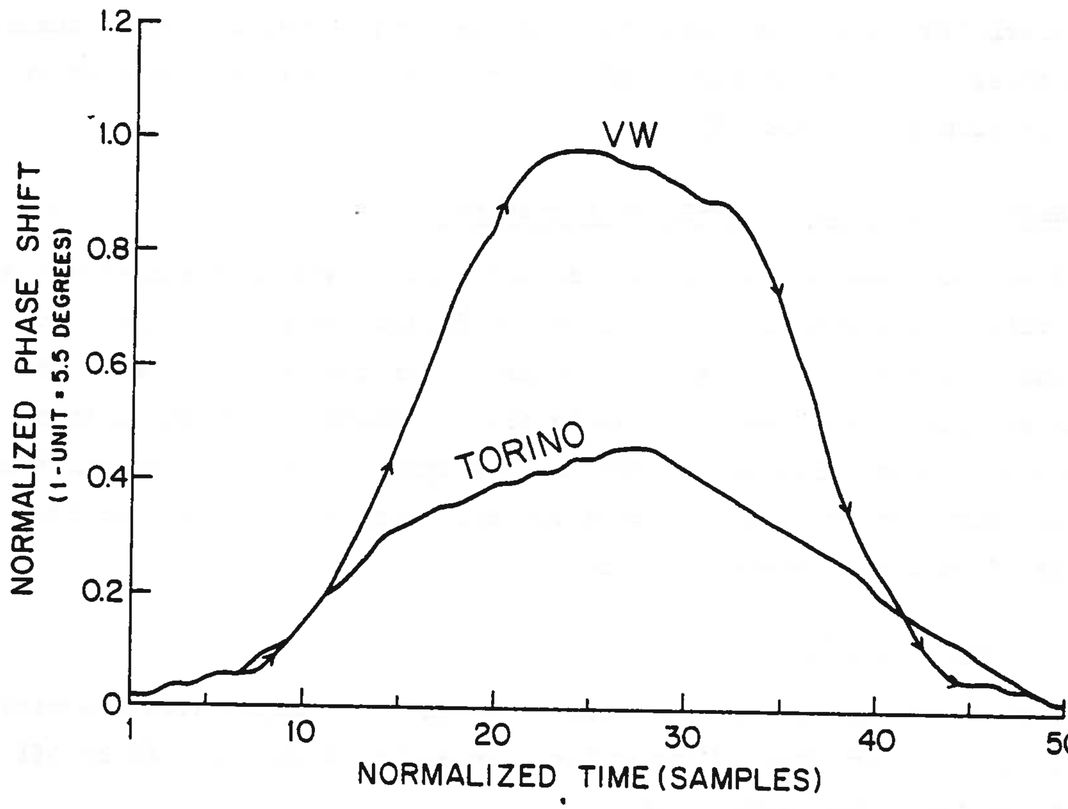

Figure 2.7 (a): Normalized Phase Signatures for Typical Cars

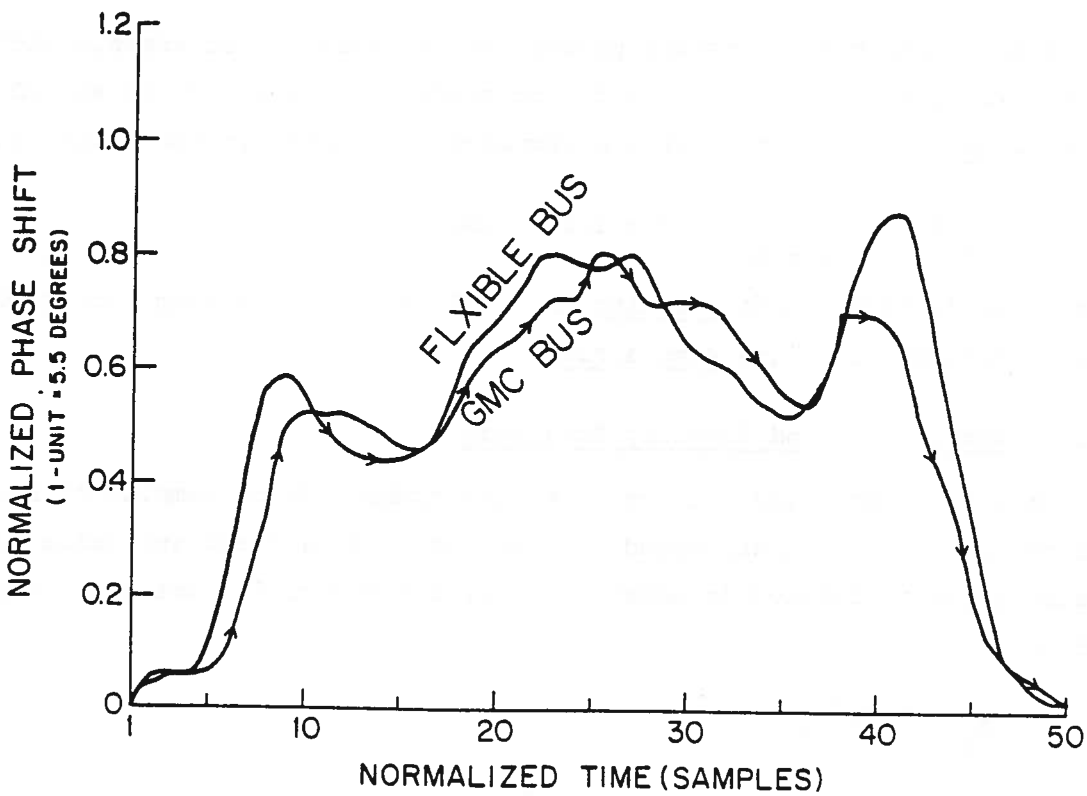

Figure 2.7 (b): Normalized Phase Signatures for Buses

where t_p = presence time (sec) for a vehicle of length ℓ traveling at speed V, and d is the effective detector length.* Thus the number of samples, N_y, actually obtained is:

$$N_y \triangleq \text{int}\left[\frac{t_p}{\Delta t}\right], \qquad (2.7)$$

where int "[·]" denotes the "greatest integer" less than argument operator. If N_{min} denotes the minimum number of samples required to perform classification in what follows, then a worst-case sampling rate which always insures at least N_{min} samples is easily shown to be:

$$\Delta t \leq \Delta t_{max} = \left[\frac{1}{N_{min}} \min_{i \in M} \left(\frac{\ell^i + d}{V^i_{max}}\right)\right], \qquad (2.8)$$

where M denotes the collection of vehicle types under consideration, ℓ^i the length of vehicle type i, and V^i_{max} its maximum expected speed. Equation (2.8) says that the maximum sampling interval which insures N_{min} samples coincides with the shortest vehicle moving at its maximum expected speed. Designing for "worst case" in this sense can result in a very large number of samples, N_y, actually received as given by (2.7). For typical presence phase-shift waveforms, such as with long slow moving vehicles, this translates into large computer-storage requirements.

2.4.3 Choice of Sample Size

The minimum required sample size, N_{min}, is a design parameter. Intuitively, we would like to make N_{min} as small as possible to minimize data storage subject to the constraint of having enough samples to be able to discriminate among the possible vehicle types. This is not a trivial tradeoff, and will be considered at length in Section 4 of this report.

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* Effective detector length is the distance measured from where the detector first responds to the front of an approaching vehicle to the point where the detector last responds to the rear of a departing vehicle. Usually, d is greater than the physical detector length. (See [4] for further discussion.)

The interpretation of (2.9) is as follows. First, $m^i(t)$ represents a nominal of reference response of the detector electronics to a vehicle of type i. As explained above, this depends in a complex way on the electromagnetic vehicle-loop interaction, and in addition, on the vehicle speed, $V^i(t)$, as it passes over the detector. $m^i(t)$ can be derived from empirical data with a typical or specific detector by passing a vehicle of known type over the loop and observing the response. An alternative interpretation is that $m^i(t)$ is the ensemble mean over all vehicles of a particular type (e.g., "cars") at time t referenced to a common speed.

The second term in (2.9), $v^i(t)$, represents the unpredictable (random) component which is not known a priori, and which is assumed to have known statistics. At this point, we assume only that $v^i(t)$ is zero-mean (if not, include $E\{v^i(t)\}^*$ with $m^i(t)$). Intuitively, $v^i(t)$ represents the combined uncertainty resulting from variations in the (speed normalized) detector response among individual vehicles of type i and signal-conditioning "noise", and a statistical approximation to such nonlinearities as threshold hysteresis.

Since we wish to deal with the sampled process, $\{y_k\}$, we will assume in the sequel that the statistics of $\{v_k^i\}$ are known, and examine the consequences of several statistical models explicitly.

2.4.6 Effects of Speed on Signature-Feature Distortion

To proceed further, two assumptions are made concerning the observation of the vehicle signature, Y:

1) the vehicle speed does not change as it passes over the detector;

2) if $y_V^i(t)$ denotes the detector response to vehicle i moving at speed V, and $y_{V'}^i(t)$ that of vehicle moving at speed $V' \neq V$, then

$$y_{V'}^i(t) = y_V^i\left(\frac{V'}{V}\, t\right) .$$

Assumption (1) is clearly an approximation, the relaxation of which is examined in Section 4, and has been justified in part by Olesik [6]. Assumption (2), also an approximation, says simply that changes in vehicle speed compress or

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*$E(\cdot)$ denotes the expected value of the argument $(\cdot)$.

3. VEHICLE CLASSIFICATION AS PROBLEM IN STATISTICAL HYPOTHESIS-TESTING

Using the normalized, sampled phase signature, we show that the problem of deciding which vehicle generated the observed phase waveform can be converted to a standard problem in multivariable hypothesis testing. The key to this approach hinges on modeling the (normalized) observation $\underline{Y} = (y_1, y_2, \ldots, y_N)$ as coming from one of M possible vehicle types. Each vehicle can generate Y according to (2.9) in a stochastic way. The only knowledge we have beforehand is that <u>given</u> a particular vehicle, the <u>statistics</u> of the signature will generate are known. From these beforehand data for different vehicles, we show how the classification problem performed via a likelihood ratio test, computed on line, from a simple function (a sufficient statistic) of the observed data sequence, Y.

3.1 Vehicle Classification in Binary Case: Problem Formulation

To simplify exposition and bring out the elements of our proposed classification methodology, we consider first the <u>binary</u> case, i.e. where there are exactly <u>two</u> vehicle types. For fixing intuition, let i = 0, 1 correspond to the hypotheses.

$H_0 \sim$ A <u>car</u> has generated Y ,

$H_1 \sim$ A <u>bus</u> has generated Y ,

where Y is the observed sampled and normalized phase shift:

$$\underline{Y} = (y_1, y_2, \ldots, y_N)^T .$$

From (2.9); if vehicle i is the actual one that generated Y, then

$$\underline{Y} = \underline{m}^i + \underline{v}^i ,$$

where

$\underline{m}^i = (m_1^i, m_2^i, \ldots, m_N^i)^T \sim$ <u>known</u> reference signature for vehicle i and when $\underline{Y} \in Z_1$, we decide "bus." Z_0 and Z_1 implicitly define a decision rule, which we select to minimize a statistical measure of the performance.

One such statistical measure of performance is the Bayes' Risk [8], which is defined to be the expected value of the cost given the decision rule. From elementary probability, we can write the expected value of the cost, $R \triangleq E(c)$, in the following manner. First, represent the as-yet unknown decision rule, $\delta(\cdot)$ via

$$\delta(Y) = \left\{ \begin{array}{l} i \quad \text{if } (Y \in Z_i) \\ i = 0,1 \end{array} \right\} , \tag{3.1}$$

where Z_0, Z_1 are subsets of R^N which make up the decision regions above (Figure 3.1). Thus whenever $\delta(Y) = 1$, we have decided a "bus" generated Y and when $\delta(Y) = 0$, a car. Then:

$$R = E(c) = \sum_{i,j} C_{ij} Pr(\delta(Y) = i|H_j) P_j \quad , \tag{3.2}$$

where

$$Pr(\delta(Y) = i|H_j) \triangleq \left\{ \begin{array}{l} \text{Probability that} \\ \underline{\text{decide}} \text{ i is true} \\ \text{given that j is} \\ \underline{\text{actually}} \text{ true} \end{array} \right\}$$

$$P_j \triangleq \left\{ \begin{array}{l} \underline{\text{a priori}} \text{ probability} \\ \text{that } H_j \text{ is true} \\ (\Sigma P_j = 1), \; P_j \geq 0 \end{array} \right\} .$$

By definition of the decision rule,

$$\begin{aligned} Pr(\delta(Y) = i|H_j) &= Pr(Y \in Z_i|H_j) \\ &= \int_{Z_i} p(Y|H_j) dY , \end{aligned} \tag{3.3}$$

and where

$$p(Y|H_j) \triangleq \left\{ \begin{array}{l} \text{conditional probability} \\ \text{density of } \underline{Y} \text{ given } H_j \\ \text{is true} \end{array} \right\} ,$$

which satisfies

$$\left.\begin{aligned} p(Y|H_j) &\geq 0 \\ \sum_j \int_{R^N} p(Y|H_j)\,dY &= 1 \end{aligned}\right\} . \qquad (3.4)$$

In terms of (3.3), some useful definitions are the (conditional) probability of false alarm, P_F, the (conditional) probability of miss, P_M, and the (conditional) probability of detection, P_D, which can be written:

$$P_F = \int_{Z_1} p(Y|H_0)\,dY = Pr(\delta(Y) = 1|H_0) \qquad (3.5)$$

$$P_D = \int_{Z_1} p(Y|H_1)\,dY = Pr(\delta(Y) = 1|H_1) \qquad (3.6)$$

$$\begin{aligned} P_M = \int_{Z_0} p(Y|H_1)\,dY &= Pr(\delta(Y) = 0|H_1) \\ &= 1 - P_D . \end{aligned} \qquad (3.7)$$

In the binary bus-car setting, P_F is the probability we decide a "bus" is present, when a car is actually there; analogous interpretations apply to P_D and P_M. Note that the total probability of error, P_E, is:

$$P_E \stackrel{\Delta}{=} P_F + P_M . \qquad (3.8)$$

From (3.3), we can evaluate the expected cost (3.2) in this binary case as:

$$\begin{aligned} E(c) &= \sum_{j=0}^{1} P_j \sum_{i=0}^{1} C_{ij} \cdot Pr(Y \in Z_i|H_j) \\ &= \sum_{j=0}^{1} P_j \sum_{i=0}^{1} C_{ij} \int_{Z_i} p(Y|H_j)\,dY . \end{aligned} \qquad (3.9)$$

3.2 Classification as Likelihood Ratio Test

To find explicitly the decision rule $\delta(\cdot)$ which minimizes (3.9), we need for $j = 0,1$

3.3 Implementation of LRT for Vehicle Classification

To implement the LRT, we need to specify the costs (C_{ij}), probability densities $p(Y|H_j)$, and the *a priori* probabilities, P_j.

3.3.1 Choosing Costs

For the "cost" in this application, there is no really obvious choice to use. One approach is to take:

$$C_{ij} = \begin{cases} C & i \neq j \ (C > 0) \\ 0 & \text{otherwise} \end{cases} \tag{3.14}$$

That is, we incur the same penalty (C > 0) for any incorrect decision, and no penalty for a correct decision. In particular, choosing C = 1, then equation (3.13) reduces to (with $C_{00} = C_{11} = 0$):

$$\Lambda(\underline{Y}) \underset{\leq}{\overset{>}{}} \frac{P_0}{P_1}, \quad \begin{matrix} \text{Say, } H_1 \text{ (bus)}, \\ \text{Say, } H_0 \text{ (car)}, \end{matrix} \tag{3.15}$$

or

$$p(\underline{Y}|H_1)P_1 \underset{\leq}{\overset{>}{}} p(\underline{Y}|H_0)P_0, \quad \begin{matrix} \text{Say, } H_1, \\ \text{Say, } H_0. \end{matrix} \tag{3.16}$$

By dividing both sides of (3.16) by

$$p(\underline{Y}) = \sum_{j=0}^{1} p(\underline{Y}|H_j), \tag{3.17}$$

and recognizing by Bayes' Theorem that

$$p(H_i|\underline{Y}) = \frac{p(\underline{Y}|H_i)P_i}{p(\underline{Y})}, \tag{3.18}$$

we see that the LRT (3.13) becomes

3.3.2 Probability Calculations in LRT and Sufficient Statistics

At the heart of implementing vehicle classification by an LRT is the conversion of the test (3.13) to a simpler computational one using a sufficient statistic. One rarely evaluates $\Lambda(\underline{Y})$ from $p(\underline{Y}|H_i)$ after obtaining the data Y, but uses a simpler function of Y, e.g., the logarithm of Λ, $\lambda(Y)$, as given by (3.11). The degree to which the required on-line data processing for classifying vehicles by a LRT can be simplified using sufficient statistics depends on the specific form of the underlying conditional probability densities that are used. For example, when $p(\underline{Y}|H_i)$ can be approximated by the exponential family of distributions, e.g., Gaussian, great simplification in the tests is possible. The example below in Section 3.4 will illustrate this.

3.4 Example of Binary Vehicle Classification Using LRT

A simple example serves to pull together the general techniques described in Section 3.3. Suppose that the signal-plus-noise model, (2.9), applies; i.e., suppose that when a car generates $y_k (i = 0)$:

$$y_k = m_k^0 + v_k^0 \quad \text{for } k = 1,2,\ldots,N \,, \tag{3.20}$$

where N is the number of (normalized) samples of $\phi(t)$, and that when a bus is present (i = 1):

$$y_k = m_k^1 + v_k^1 \quad \text{for } k = 1,2,\ldots,N \,. \tag{3.21}$$

By assumption, the $\{m_k^i\}$ are the known or "reference" parts of the signature and $\{v_k^i\}$ are the unknown or stochastic components. We can think of the $\{v_k^i\}$ as being a zero-mean* sequence of random variables; i.e.:

$$E(v_k^i) = 0 \,, \quad k = 1,2,\ldots,N \qquad i = 0,1 \tag{3.22}$$

The v_k^i can be specified probabilistically via their joint (conditional) probability density function,

---

* If $E(v_k^i) \neq 0$, just include with $\{m_k^i\}$.

$$p(\underline{v}|H_i) = \frac{1}{(2\pi)^{N/2}(\det \Sigma_i)^{1/2}} \exp[-\frac{1}{2}\underline{v}^T \Sigma_i^{-1} \underline{v}] . \tag{3.27}$$

From (3.27), for the special case where the v_k^i are independent for all k, Σ_i is a diagonal matrix, whose (k,k) entry is $(\sigma_k^i)^2$ and zero elsewhere, $k = 1,\ldots,N$. Then (3.27) reduces to (3.26).

To obtain $p(\underline{Y}|H_i)$ from $p(\underline{V}|H_i)$ is straightforward in this case due to the linearity of the model. In particular since the m_k^i are assumed known, it follows that

$$p(y_k|H_i) = p(v_k|H_i)\Big|_{v_k = y_k - m_k^i} , \tag{3.28}$$

or from (3.21)

$$p(y_k|H_i) = \frac{1}{\sqrt{2\pi\sigma_k^i}} \exp[-\frac{1}{2}\frac{(y_k - m_k^i)^2}{(\sigma_k^i)^2} , \tag{3.29}$$

or from (3.26) and (3.27) in the multivariate case,

$$p(\underline{Y}|H_i) = p(y_1,\ldots,y_N|H_i)$$

$$= \frac{1}{(2\pi)^{N/2}[\det \Sigma_i]^{1/2}} \exp[-\frac{1}{2}(\underline{Y} - \underline{m}^i)^T \Sigma_i^{-1} (\underline{Y} - \underline{m}^i) ; \tag{3.30}$$

i.e., $\underline{Y} \sim N(\underline{m}^i, \Sigma_i)$ where $\underline{m}^i = (m_1^i, m_2^i, \ldots, m_N^i)^T$ and Σ_i is the covariance of $\underline{v}^i$ given above. We note that (3.30) applies whether or not the $\{v_k^i\}$ sequence is independent for $k = 1,2,\ldots$.

From (3.30), the likelihood ratio, $\Lambda(\underline{Y})$, equation (3.6), can now be computed:

$$\Lambda(\underline{Y}) = \frac{p(\underline{Y}|H_1)}{p(\underline{Y}|H_0)}$$

$$= \frac{\frac{1}{(2\pi)^{N/2}|\Sigma_1|^{1/2}} \exp[-\frac{1}{2}(\underline{Y} - \underline{m}^1)^T \Sigma_1^{-1} (\underline{Y} - \underline{m}^1)]}{\frac{1}{(2\pi)^{N/2}|\Sigma_0|^{1/2}} \exp[-\frac{1}{2}(\underline{Y} - \underline{m}^0)^T \Sigma_1^{-1} (\underline{Y} - \underline{m}^0)]} . \tag{3.31}$$

Binary Classification Algorithm, Gaussian Case

1) Obtain the normalized (sampled) phase shift measurement,

$$\underline{Y} = (y_1, y_2, \ldots, y_N).$$

2) Compute the (scalar valued) statistic:

$$\ell(\underline{Y}) = \frac{1}{2}\,\underline{Y}^T Q \underline{Y} + \underline{Y}^T \underline{r} \quad , \tag{3.36}$$

where

$$Q = (\Sigma_0^{-1} - \Sigma_1^{-1})_{N\times N}$$

$$\underline{r} = (\Sigma_1^{-1}\,\underline{m}^1 - \Sigma_0^{-1}\,\underline{m}^0)_N$$

are precomputable given

$$p(\underline{Y}|H_i) \sim N(\underline{m}^i, \Sigma_i).$$

3) Compare

$$\ell(\underline{Y}) \text{ to } \hat{\eta},$$

where $\hat{\eta}$ is precomputable using (3.34):

a) If $\ell(Y) \geq \hat{\eta}$ then decide "BUS" ($\delta(Y) = 1$)

b) If $\ell(Y) < \hat{\eta}$ then decide "CAR" ($\delta(Y) = 0$).

4) Go back to "1" for next vehicle.

A block diagram for this algorithm is shown in Figure 3.2.

4. PRACTICAL IMPLEMENTATION FOR M-VEHICLE CASE

In this section, we address several aspects of the practical application of LRT classification techniques. As stated in Section 1, it is desired to demonstrate the classification procedure over a wider class of vehicles than two. In Section 4.1, a maximum a posteriori probability (MAP) or maximum likelihood (ML) test is proposed for the M-vehicle case. To implement this test requires a means for calibration and speed normalization of received signatures. Methods for doing this are proposed in Section 4.2. For a general statistical signature model, calculations in the LRT can be complex. Therefore in Section 4.2, we suggest several possible approaches to simplify on-line calculations of relevant sufficient statistics in the LRT. Finally in Section 4.3, we present a simulation of the classification algorithm using 10 different vehicle types and examine the resulting performance.

4.1 Extension of Likelihood Tests to M-Vehicle Case

4.1.1 MAP/ML Classification Algorithm

To apply an LRT to the general M-vehicle case is feasible in principle but complicated by the problem of finding the M-decision regions, $\{Z_i\}$, in equation (3.1), and the corresponding decision rule, $\delta(\cdot)$. We will not pursue the general methods here, and will focus on one which results with a reasonable cost choice for the Bayes Risk. In particular, if we let all incorrect classifications have equal cost, and correct decisions have zero cost; i.e.:

$$C_{ij} = \begin{cases} C > 0 : i \neq j \\ 0 \quad : i = j \end{cases} , \tag{4.1}$$

then the decision rule which minimizes R can easily be derived similar to (3.18), (3.19) (see; e.g., [8]):

1) obtain the sampled (normalized) signature $\underline{Y}$,

3) find $\hat{i}$ which maximizes (4.5), and

4) then, $\delta(Y) = \hat{i}$. (4.6)

Note that just as in the binary case, the effect of the a priori probabilities is to bias the decision toward whichever hypothesized vehicle is most likely beforehand. It is not likely in practice that any vehicle type can be assigned meaningful a priori probabilities. By taking $P_i = \frac{1}{M}$ for all i, the $\{P_i\}$ can be ignored in (4.5), in which case (4.6) is an ML decision rule. In either case, the only calculation in (4.5) which must be carried out on line is the quadratic form which involves $\underline{Y}$ in (4.5). For example, if we further assume that

$$\Sigma_i = [I]^*_{NxN}\sigma_i^2 , \qquad (4.7)$$

which is equivalent to saying that

$$p(\underline{Y}|H_i) = N(\underline{m}^i,[I]\sigma_i^2), \qquad (4.8)$$

or that each sample, y_k, given that it is generated by vehicle i, has mean m_k^i and variance $(\sigma^i)^2$ independent of k. Substituting (4.7) into (4.5) results in

$$\lambda_i(\underline{Y}) = \ell n P_i - N\ell n\sigma_i - \frac{1}{2\sigma_i^2}(\underline{Y} - \underline{m}^i)^T(\underline{Y} - \underline{m}^i), \qquad (4.9)$$

or

$$\lambda_i(\underline{Y}) = \ell n P_i - N\ell n\sigma_i - \frac{1}{2\sigma_i^2}\sum_{k=1}^{N}(Y_k - m_k^i)^2, \qquad i = 1,2,\ldots,M. \qquad (4.10)$$

For each i, (4.10) can be calculated (in parallel) independently and recursively as the y_k become available, by introducing an "accumulator" variable:

$$w_k^i = w_{k-1}^i + (y_k - m_k^i)^2 , \qquad (4.11)$$

with $w_0^i \equiv 0$, we see that (4.11) at k = N, w_N^i, is simply the quadratic form in (4.9):

$$w_N^i = \sum_{k=1}^{N}(Y_k - m_k^i)^2, \qquad (4.12)$$

---

* $[I]_{NxN}$ is the (NxN) identity matrix.

with the aid of (4.11), we can view the classification algorithm in a sequential, parallel process form as shown in Figure 4.1. The significance of this realization is the efficiency that can be introduced where pipelined processing is available in the computer hardware.

4.2 Calibration and Normalization of Sampled Signature Model

To implement either the binary or vehicle classification tests requires the designer to:

1) select a specific probability distribution $p(Y|H_i)$ for each vehicle type, based on experimental data;

2) choose the sample size, N, used in classification algorithms;

3) provide a sampling procedure which converts the analog signature received into N (uniformly spaced) samples; and

4) develop methods to simplify required on-line calculations using sufficient statistics and approximations to the (sampled) signature models.

Each of these tasks has at least some impact on the other with many resulting overall performance tradeoffs possible. For example, we have used Gaussian signature models to illustrate the tests, which lead to very easy to implement algorithms in terms of required on-line calculations. If the signature models are not Gaussian, the calculations may become more complex. With respect to sample size (N), the tradeoff is one of data storage and computation time (and complexity) when N is large, against inaccuracy of the tests when N is small. We make no attempt to provide definitive answers to these very difficult tradeoff questions, but suggest some general guidelines as appropriate.

4.2.1 Estimation of Signature Statistics

To proceed with an implementation of the proposed tests, one must first have the statistical signature model, as parameterized by $p(\underline{Y}|H_i)$, for each vehicle type i. As observed in Section 2, the phase shift waveform received depends primarily on the vehicle type and its speed. To a lesser extent, it depends on the vehicle's lateral position over the sensor [2]. Also, the peculiarities of the specific detector installation site will impact on the

Recall that this conservative choice can lead to a very large number, N_y, of actual samples, e.g., when a long, slow moving vehicle passes over the detector. If computer storage is not an issue, then a normalization procedure to obtain N_{MIN} points is easy:

1) given N_{MIN}, $\Delta t = \Delta t_{max}$ from (2.8),

2) store the $N_y = \text{int}[\frac{\Delta t}{tp}]$ points $\{y_k\}$ associated with the passage of the unknown vehicle,

3) select one out of every int $[N_y | N_{MIN}]$ points and label as a normalized array; i.e., if

$$y(i) = \text{i-th sample, } i = 1,2,\ldots,N_y ,$$

then,

$$y_N(j) = y(\text{int } [\frac{N_y}{N_{MIN}}]j - 1) \ . \tag{4.13}$$

For example, if $N_y = 8$ and $N_{MIN} = 4$, then, (4.13) becomes:

$$y_N(j) = y(zj - 1) \ , \tag{4.14}$$

or

$$\left.\begin{aligned} y_N(1) &= y(1) \\ y_N(2) &= y(3) \\ y_N(3) &= y(5) \\ y_N(4) &= y(7) \end{aligned}\right\} . \tag{4.15}$$

This procedure will provide N_{MIN} uniformly spaced samples of the received signatures y(t). Further, note that we will not actually need storage for the y_N array, since we can keep track of it with a simple "pointer" using the argument of (4.13).

The big problem with this straightforward approach is that we have found the required N_{MIN} to do accurate classification is <u>very</u> much smaller than the typical N_y obtained with Δt_{max} ($\frac{N_y}{N_{MIN}} \simeq 200$). This results in very inefficient use of available computer memory. An alternative approach to normalization with <u>fixed</u> memory size approximately equal to 2 N_{MIN} is described in Appendix B. The

This procedure, while straightforward and systematic, may not be computationally easy when the $p(Y|H_i)$ are other than Gaussian, since P_E is hard to calculate. Thus one is inevitably led to obtaining some kind of bound on P_E or $E(c)$ which depends on N. A number of possible bounds are currently being investigated by Sylvester [7]. For the simulated examples studied in Section 4.3, we will show how N affects the performance of the tests as a function of noise level in the received signature. See references [7] and [8] for development of more precise bounds.

4.3 Performance Evaluation

In this section, we demonstrate the performance of the proposed ML and MAP algorithms by simulation. Reference phase-shift signatures have been obtained for 10 different vehicle types from reference [2] (see Appendix A). A Monte-Carlo simulation has been constructed by adding pseudo-random noise to the reference signatures and evaluating the ML classification algorithm described in Section 3.4.

4.3.1 Case Study Vehicle Mix

To demonstrate the ML/MAP classification algorithm performance, we have performed a simulation using vehicle signature models from reference [2]. To demonstrate with reasonable spectrum of vehicle types, the following 10 have been selected (see Appendix A):

1) VW Sedan (Car)
2) Ford Torino (Car)
3) GMC Bus (Bus)
4) Flxible Bus (Bus)
5) Moving Van (Truck)
6) Panel Truck (Truck)
7) Truck "1" (Truck)
8) Truck "2" (Truck
9) Tractor Trailer(Truck)
10) Motorcycle (Misc.) .

These vehicles provide a benchmark of types that are likely to be found on surface streets. Our objective was to obtain some sense of how sensitive the

This gives a simulated random sample of the signature $\underline{Y} = (y_1,\ldots,y_N)$,

4) given the simulated signature sample in (3), compute

$$\lambda_i(\underline{Y}) = \ln P_i - \frac{1}{2}\ln|\Sigma_i| - \frac{1}{2}(\underline{Y} - \underline{m}^i)^T \Sigma_i^{-1} (\underline{Y} - \underline{m}^i) \quad (4.17a)$$

$$= \ln P_i - N \ln {}_i - \frac{1}{2\sigma_i^2} \sum_{k=1}^{N} (y_k - m_k^i)^2, \quad (4.17b)$$

and

5) pick $\hat{i} = \max_i \lambda_i(Y)$, $i = 1,2,\ldots,10$.

Since no a priori data for the noise statistics have been available, we have studied noise effects for simulation purposes parametrically. This is done by

1) finding the peak amplitude for each reference signature from the data in Appendix A,

2) using the peak-value from (1) as the largest simulated noise level variance, $(\sigma^i_{MAX})^2$, and

3) for each i, varying the simulated noise level between 0 and $(\sigma^i_{MAX})^2$.

For example, for a Flxible Bus, Figure A-1 shows that the peak phase shift is (approximately) (0.8)x*55 degrees) = 44 degrees. We then take $\sigma^2_{MAX} = 44$ or $\sigma_{MAX} = \sqrt{44} = 6.6$. Note that the 3-σ 95 percent uncertainty interval is then $\pm$ 19.9 degrees of phase or 45 percent of the peak. We have found that noise levels higher than this totally obliterate recognizable features. Figure 4.2 gives a typical sampled signature when $\hat{\sigma}$ is selected to be 10 percent of σ_{MAX}. In the simulation results that follow, for each vehicle type we have varied the simulated noise variance as a percentage of this maximum variance.

Define $\hat{\sigma}$ to be the (normalized) (percent) of maximum variance, $0 \leq \hat{\sigma} \leq 100$, then the actual variance is:

$$\sigma^i = \left(\frac{\hat{\sigma}}{100}\right)\sigma^i_{MAX} \quad ;$$

with this change of variable, we can compare all results as a function of $\hat{\sigma}$.

4.3.3 Results

A Monte-Carlo simulation has been conducted with 1000 trials of the algorithm steps (1)-(5) from Section 4.3.2. In each case, the actual classification outcome, i, and the true vehicle type, i, are recorded. For each vehicle type, the simulation records the relative frequency of detection, defined as:

$$P_D = \frac{\text{total number of correct classifications with } i = 1}{\text{total number of trials when actual vehicle is } i} ,$$

and the relative frequency of false alarm defined as:

$$P_F = \frac{\text{total number of incorrect classifications with } i = i}{\text{total number of trials when actual vehicle is } j \neq 1} .$$

Using a sample size of N = 50, and 1000 trials, P_D and P_F are plotted as functions of the normalized noise standard deviation, $\hat{\sigma}$, in Figures 4.3(a) through 4.12(a), corresponding to each of the 10 possible vehicle types. That is, P_d represents the relative percent of the 1000 trials in which the true vehicle present is i, and it is correctly classified as such.

Some general comments on the simulation results are appropriate. In most cases, even when the signatures are corrupted by as much as 20 percent noise, detection probabilities exceed 90 percent, with false-alarm rates less than 1 percent.

An alternative picture of performance can be obtained by examining the relative distribution of classifications, with the true vehicle as a parameter, as shown in Figures 4.3(b) through 4.12(b). For example, by examining the distribution of outcomes when the true vehicle is a Volkswagen sedan (Figure 4.3(b)), we see that in the 1000 trial Monte-Carlo simulations, the relative frequency of misclassification is below 80 percent even when the noise level exceeds 50 percent (normalized). Even in the very high noise case, the misclassifications tend to cluster, in this case between moving van and truck. Improvements against these types of misclassification may be obtained by using heuristic outlier tests. For example, the vehicle speed can be estimated from the present pulse (see Section 2), assuming the vehicle length corresponding to the classification outcome. A check for consistency of the classification will then be to compare this estimated speed with prevailing mean speed of vehicles observed during the recent past.

Since a principle application of the classification algorithm may be in bus-prioritized intersection control, it is interesting to examine the simulation outcomes with respect to bus classification. For the two types of

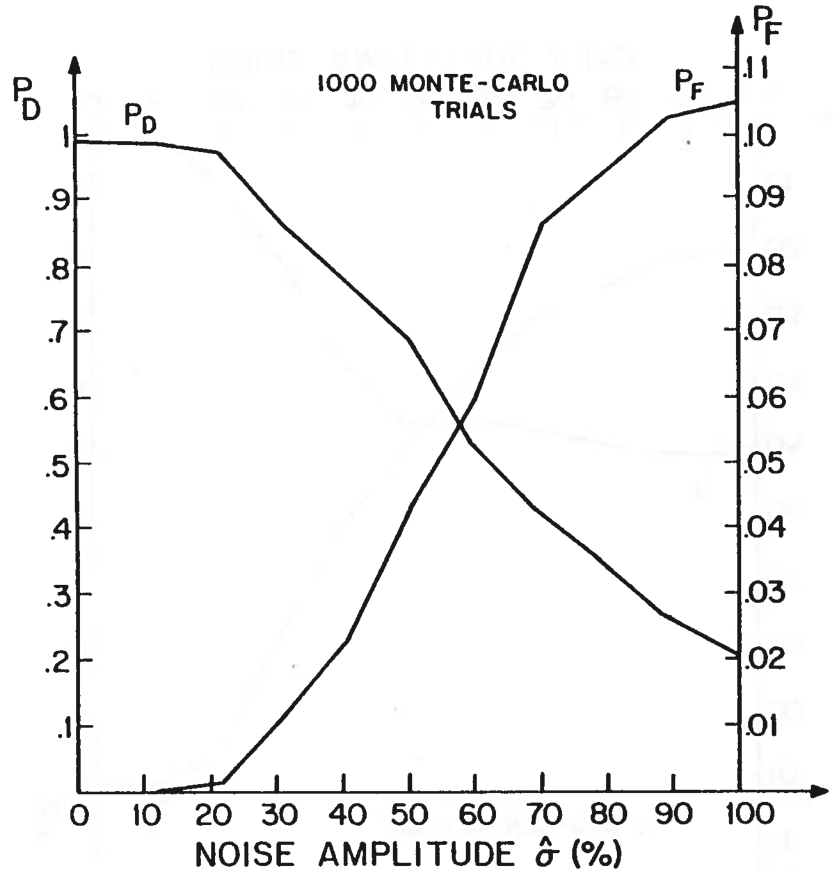


Figure 4.4(a): Simulated Detection and False Alarm Frequencies When True Vehicle Is Ford Torino

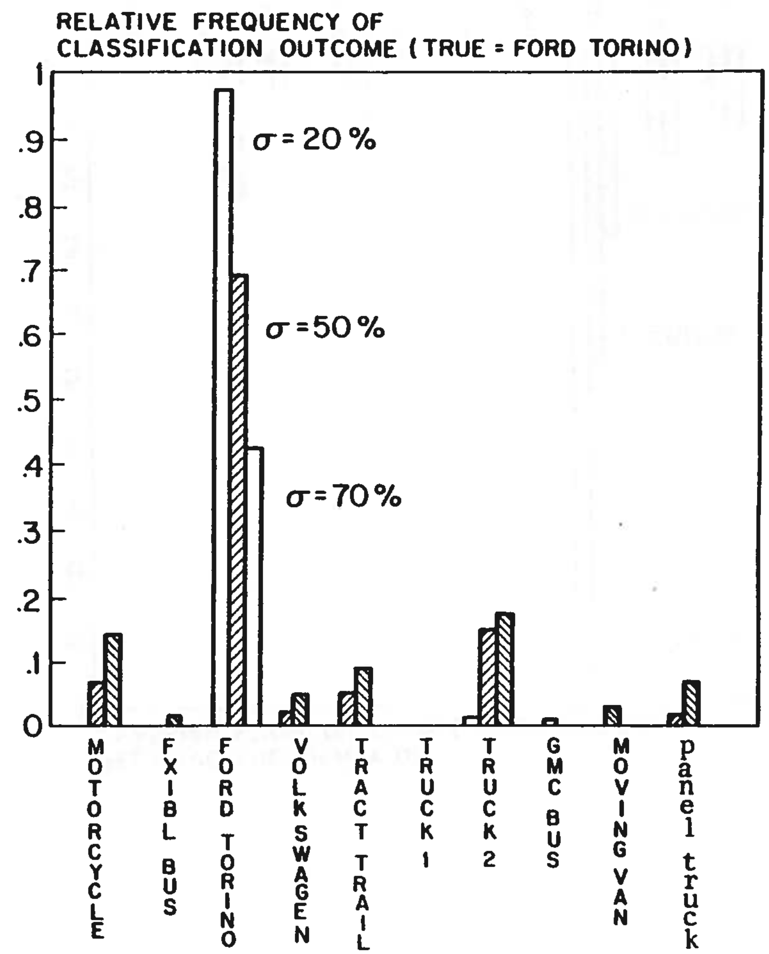


Figure 4.4(b): Distribution of Classification in Simulation When True Vehicle Is Ford Torino

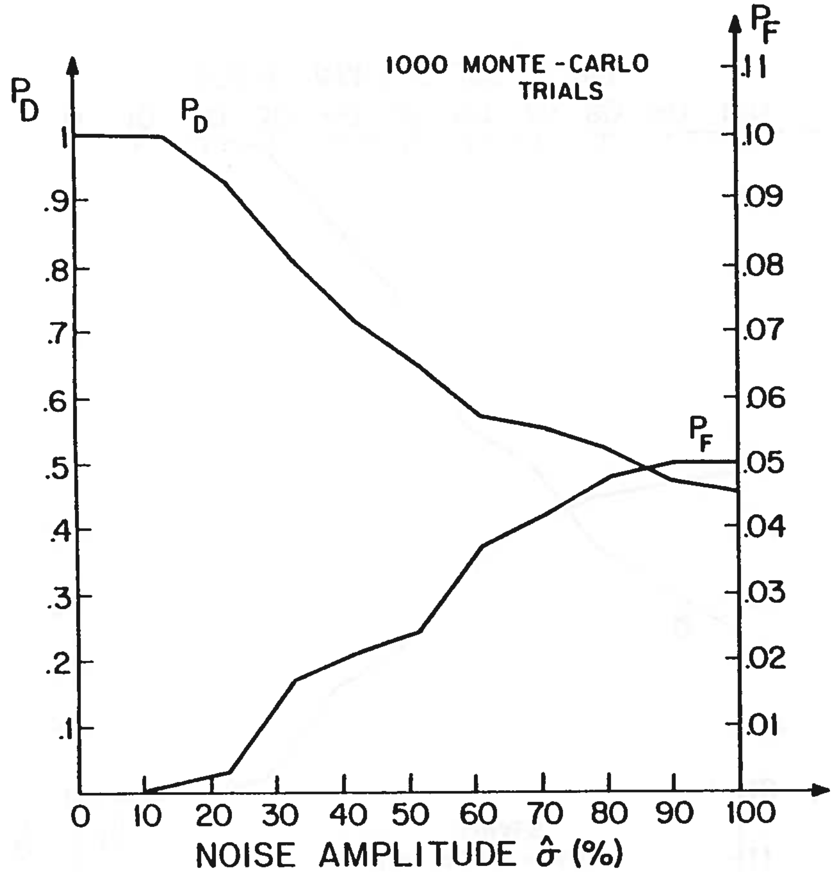


Figure 4.6(a): Simulated Detection and False Alarm Frequencies When True Vehicle Is Flxible Bus

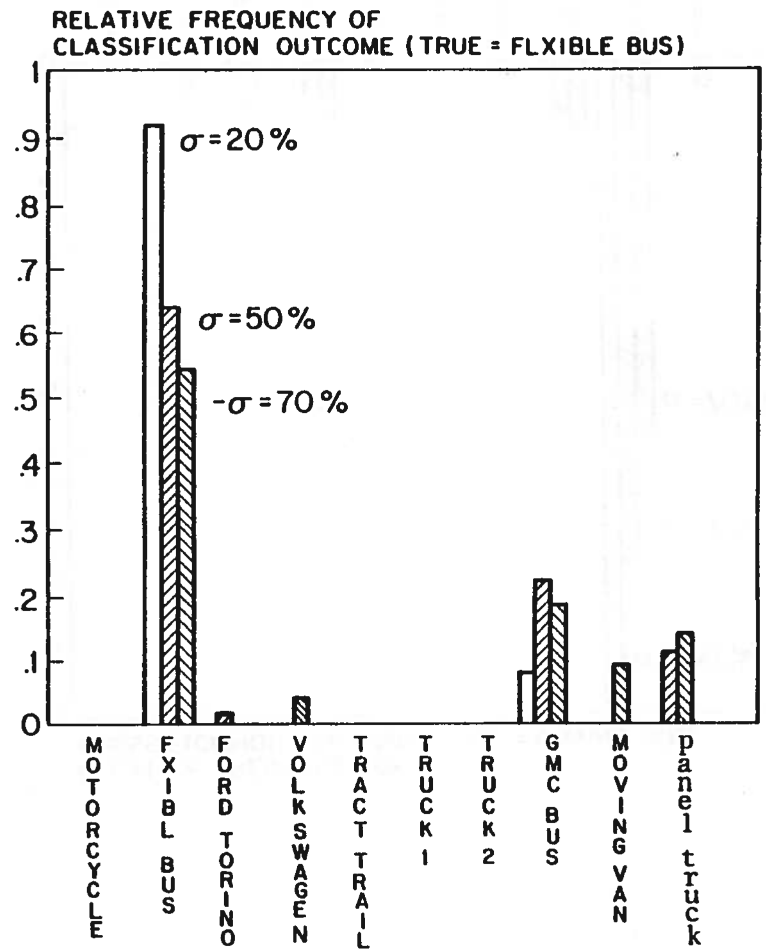


Figure 4.6(b): Distribution of Classification in Simulation When True Vehicle Is Flxible Bus

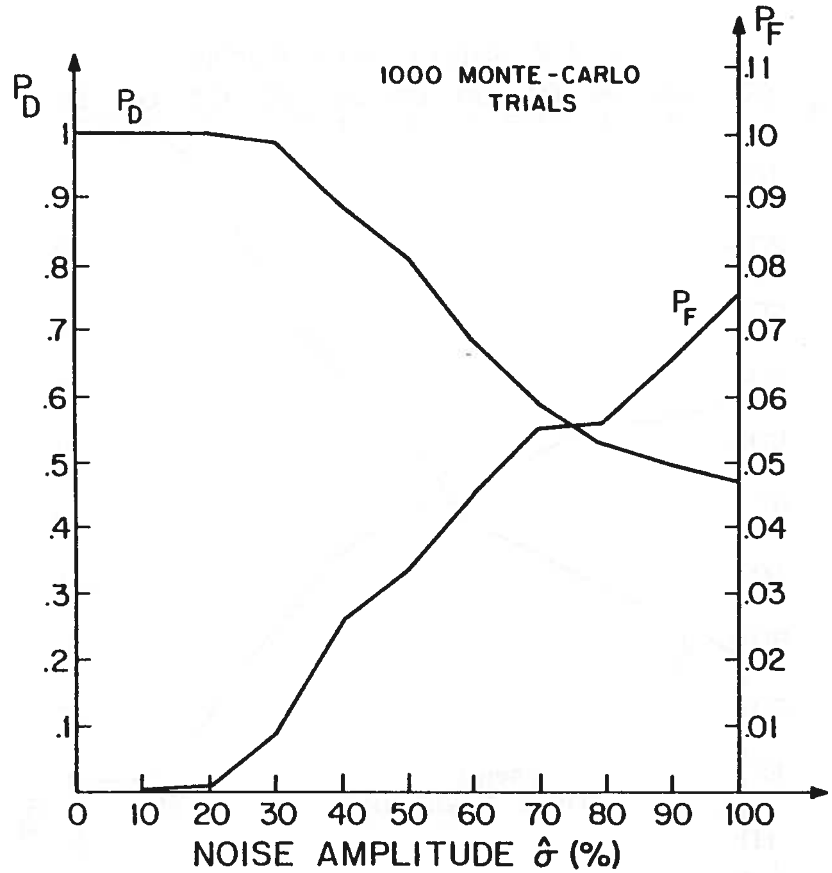


Figure 4.8(a): Simulated Detection and False Alarm Frequencies When True Vehicle Is Van (Panel Truck)

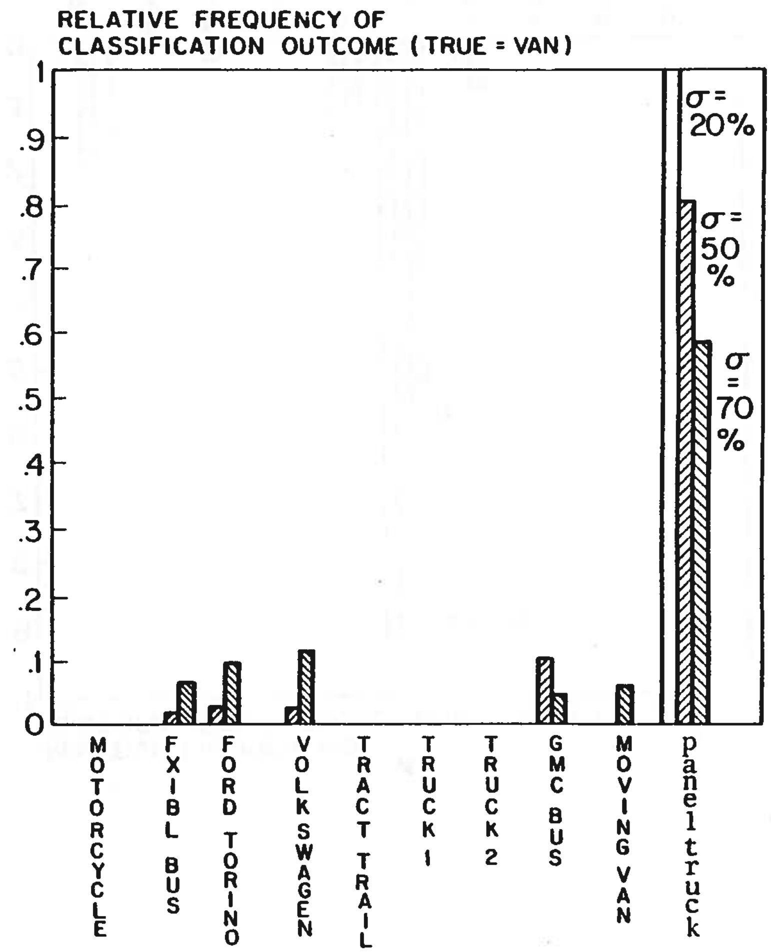


Figure 4.8(b): Distribution of Classification in Simulation When True Vehicle Is Van (Panel Truck)

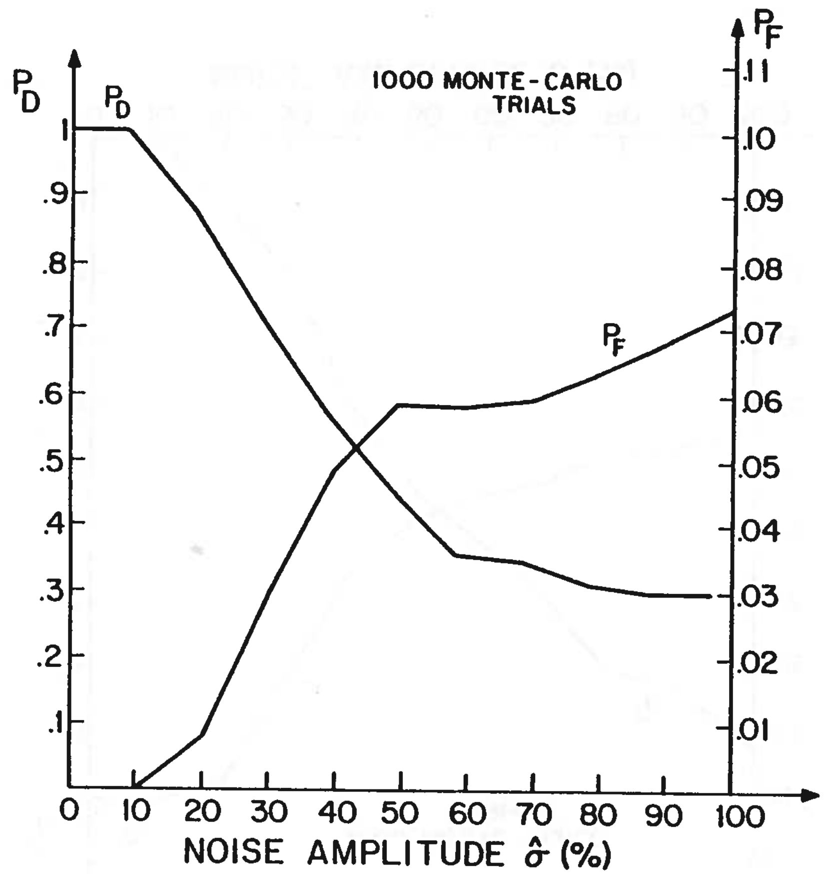


Figure 4.10(a): Simulated Detection and False Alarm Frequencies When True Vehicle Is Truck 2

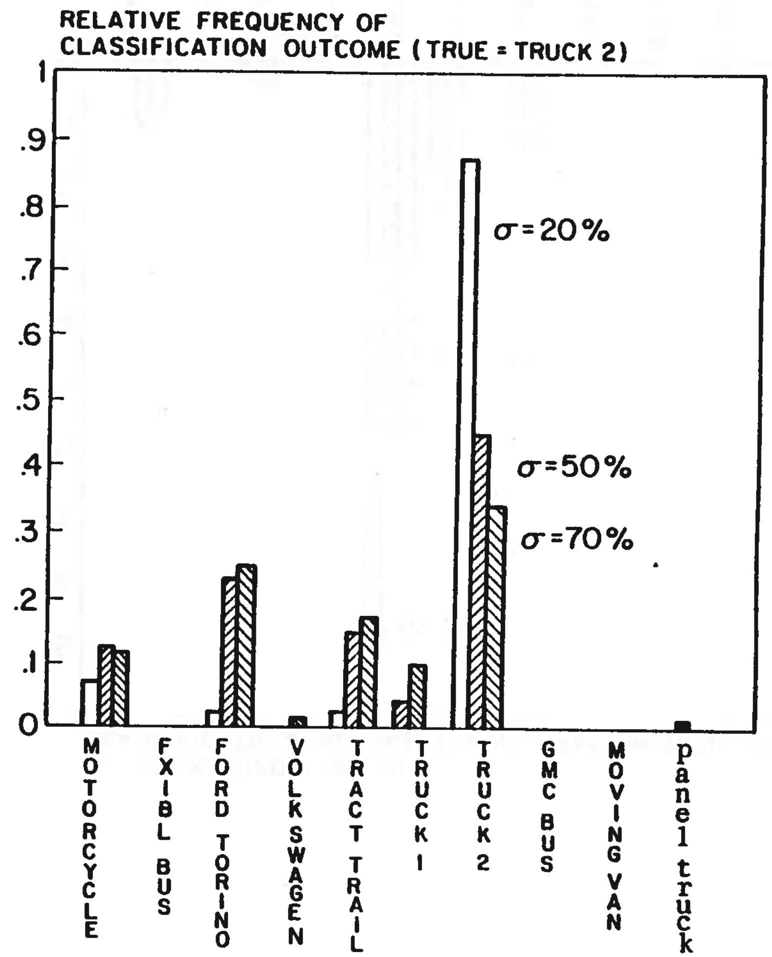


Figure 4.10(b): Distribution of Classification in Simulation When True Vehicle Is Truck 2

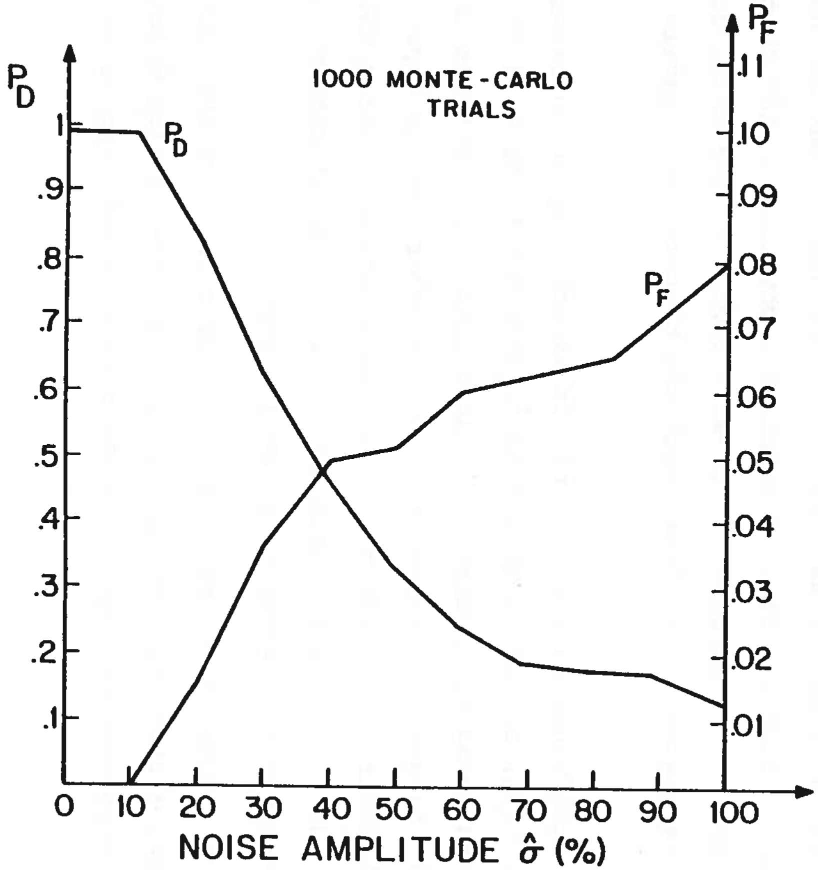


Figure 4.12(a): Simulated Detection and False Alarm Frequencies When True Vehicle Is Motorcycle

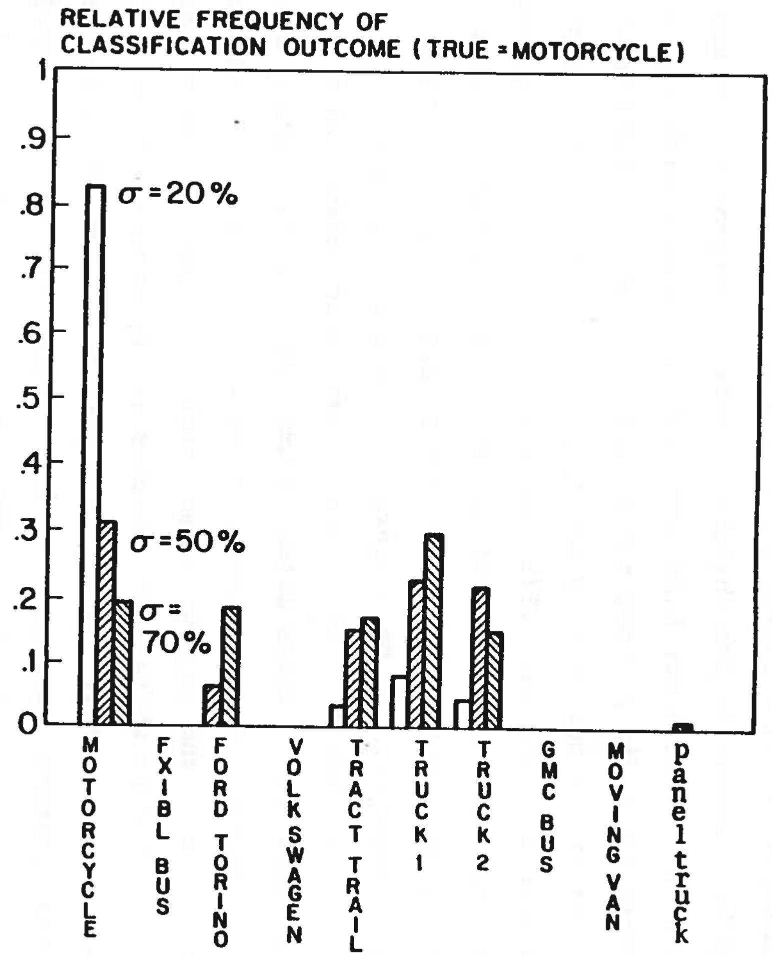


Figure 4.12(b): Distribution of Classification in Simulation When True Vehicle Is Motorcycle

Figure 4.13 shows the effect on P_D of reducing the sample size to N=30, while keeping all other parameters the same. As expected, the sensitivity to sample size increases at higher noise levels. However, doubling the sample size to N=100 has yielded negligible improvement over the results obtained for N=50. Our empirical experience with this signature collection tends to indicate a relative insensitivity of classification performance above N=40 samples per signature. However, since this result applies only to our simulated statistical model, it is erroneous to draw general conclusions from this result. A procedure for optimizing the choice of N with respect to various performance criteria is currently being performed by Sylvester [7] using the notion of statistical "distance" measures [8], which can be computed once the more precise statistical model for the signatures has been obtained by experiment.

5. CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

A simple approach to passive vehicle classification using digitally sampled loop-detector phase-shift information has been proposed. Using a normalized sampled representation of the signature, a classification algorithm has been developed based on classical statistical hypothesis-testing methods. Depending on the a priori data available to describe the signatures and relative frequency of vehicles, the tests have a Bayesian or maximum likelihood interpretation. Computationally, each type of test involves a likelihood ratio or likelihood function calculation which can often be greatly simplified through the use of sufficient statistics.

Initial evaluation of the techniques proposed using a simulation shows that a fairly broad spectrum of vehicle types can be both identified and distinguished from one another in the equivalent of low to moderate additive noise. Our proposed signature model and subsequent simulation employed an additive "signal-plus-noise" decomposition of the loop-detector phase-shift response. The noise component is viewed to combine the statistical variation of the vehicle signature among vehicles of the same or similar type together with any actual electronic or signal-processing "noise" in the usual sense.

An advantage of this decomposition is that site-specific variations in detector geometry, sensitivity, and qualitative feature response can be calibrated out in a reasonably simple and systematic way. In any case, we emphasize that the approach in not restricted to vehicle signatures modeled as signal plus additive white Gaussian noise. Both non-Gaussian and correlated signature sequences are admissible to the extent that one can compute the appropriate likelihood function required for the test. Whenever simpler exponential families of probability distributions can be used to approximate the underlying signature model however, considerable simplification of required on-line calculation can be achieved through the use of sufficient statistics for the required likelihood functions. Several examples in the Gaussian case are given to illustrate typical simplifications possible, fitted to the reference signature.

Further evaluation of the methods proposed here for vehicle classification is seen to require a blend of experiment and analysis of the computational requirements versus capabilities dictated by the specific hardware cinfiguration that the designer uses. An advantage of the statistical approach in the application is that many of the design tradeoffs, such as sample-size selection, signature model choice, and likelihood function evaluation, can be carried out in a systematic fashion using many powerful tools from statistical hypothesis-testing and communication theory, in the context of whatever digital technology is used, from micro to mini-computer.

APPENDIX A

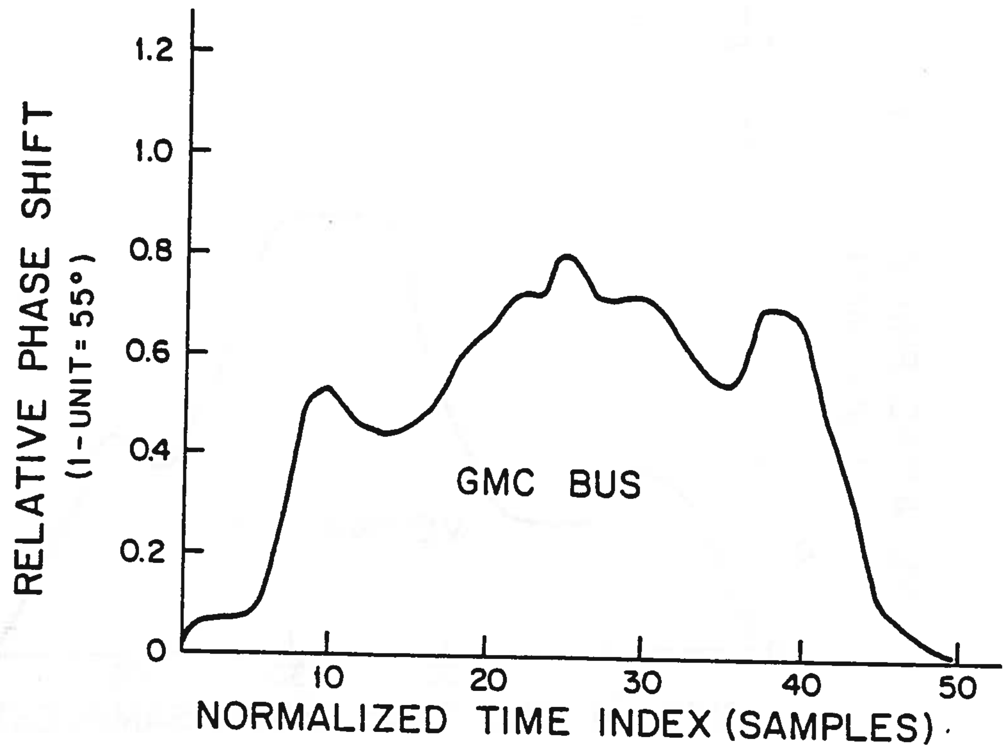
SAMPLE VEHICLE SIGNATURES

This appendix contains phase signatures from Reference [2] for 10 different vehicle types used in this report. The vehicles are indexed as shown in Table A-1.

Table A-1: Vehicle Types Used in Simulation Studies

Index i	Vehicle Description	Type	Figure	Page
1	VW Sedan	Car	A-1	64
2	Ford Torino	Car	A-1	64
3	GMC Bus	Bus	A-2	65
4	Flxible Bus	Bus	A-2	65
5	Moving Van	Truck	A-3	66
6	Panel Truck	Truck	A-3	66
7	Truck "1"	Truck	A-4	67
8	Truck "2"	Truck	A-4	67
9	Tractor Trailer	Truck	A-5	68
10	Motorcycle	Misc.	A-5	68

Each signature is shown with a common (normalized) reference speed, with a 50 sample quantization (N_y = 50). Amplitudes are normalized to the peak phase shift over all 10 signatures to show true relative amplitude.



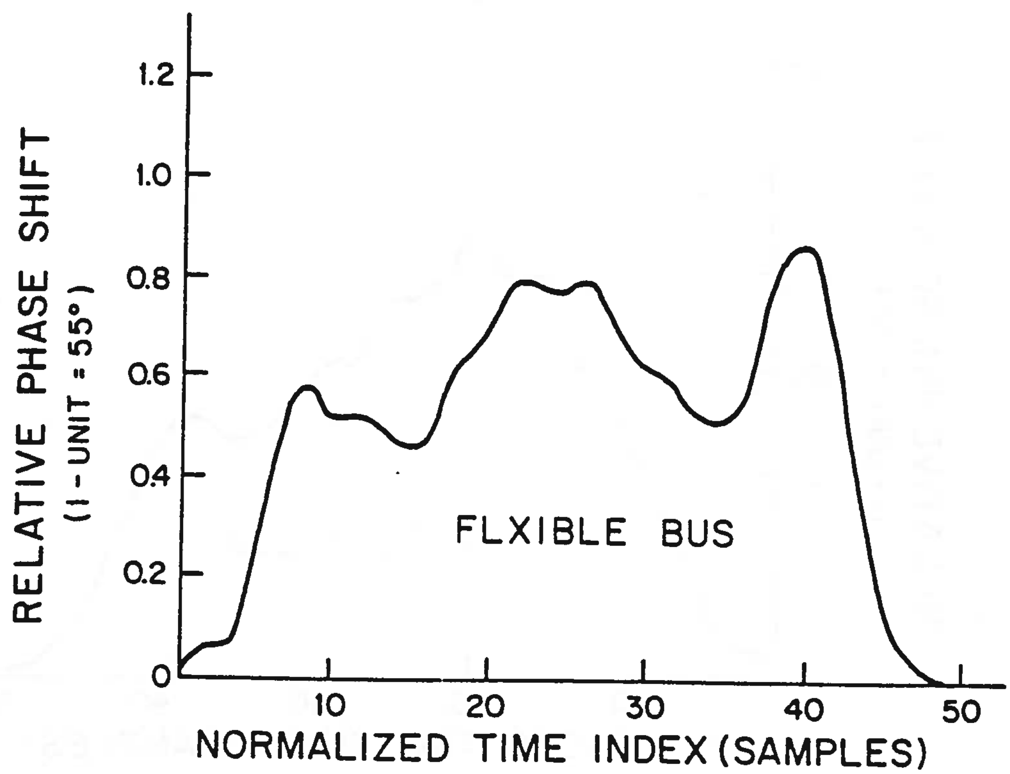
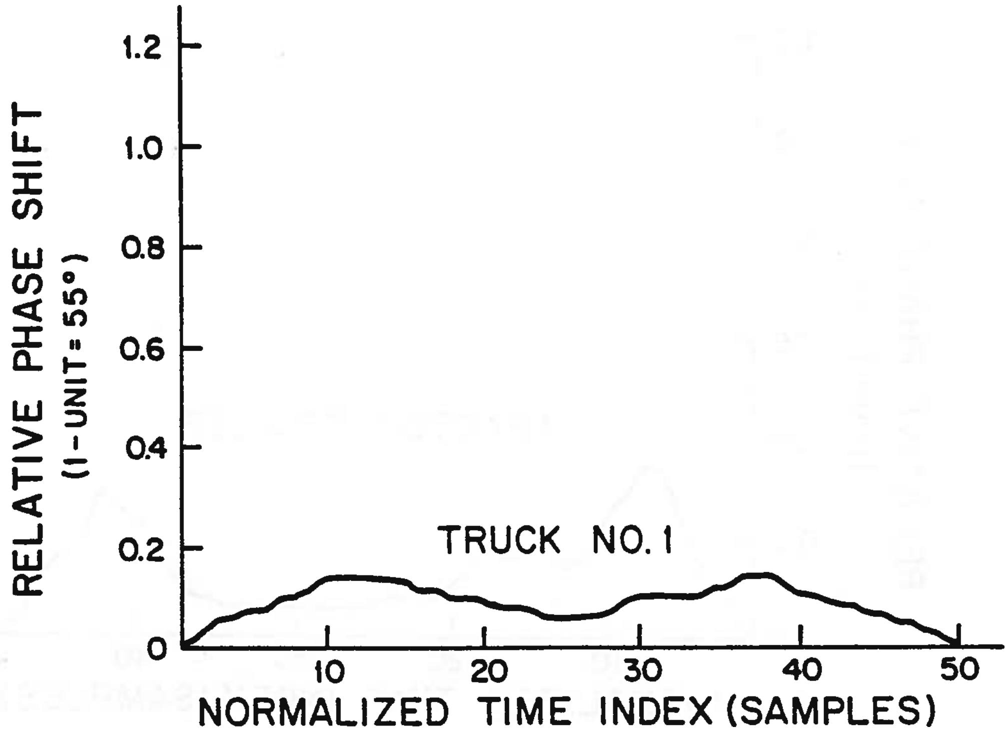


Figure A-2: Normalized Phase Signatures for GMC and Flxible Buses



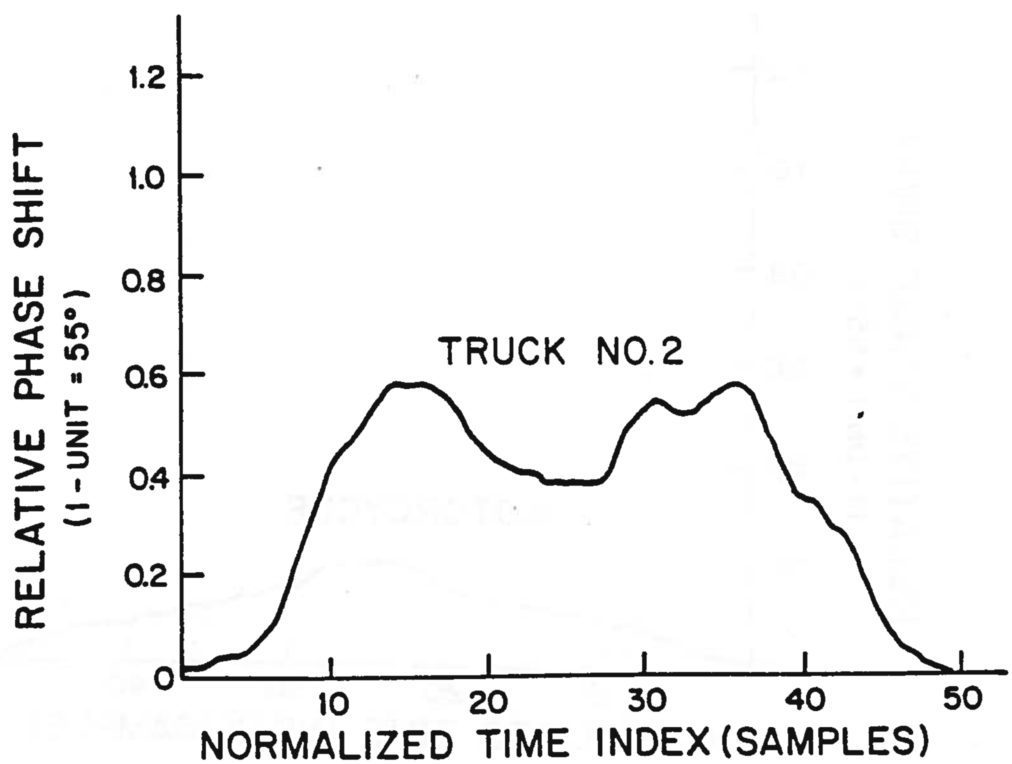


Figure A-4: Normalized Phase Signatures for Two Miscellaneous Truck Types

APPENDIX B

PROGRAM FOR NORMALIZED DATA STORAGE

This appendix is a block diagram of the logic for obtaining a normalized sampled phase shift signature with at least N_{MIN} points. Memory size is assumed to be 2^N words, with N an integer design parameter, satisfying $N \geq \log(\frac{N_{MIN}}{2})$. Figure B-1 illustrates the data storage procedure. Figure B-2 illustrates that data reconstruction procedure to obtain the samples in the sequence in which they have been received.

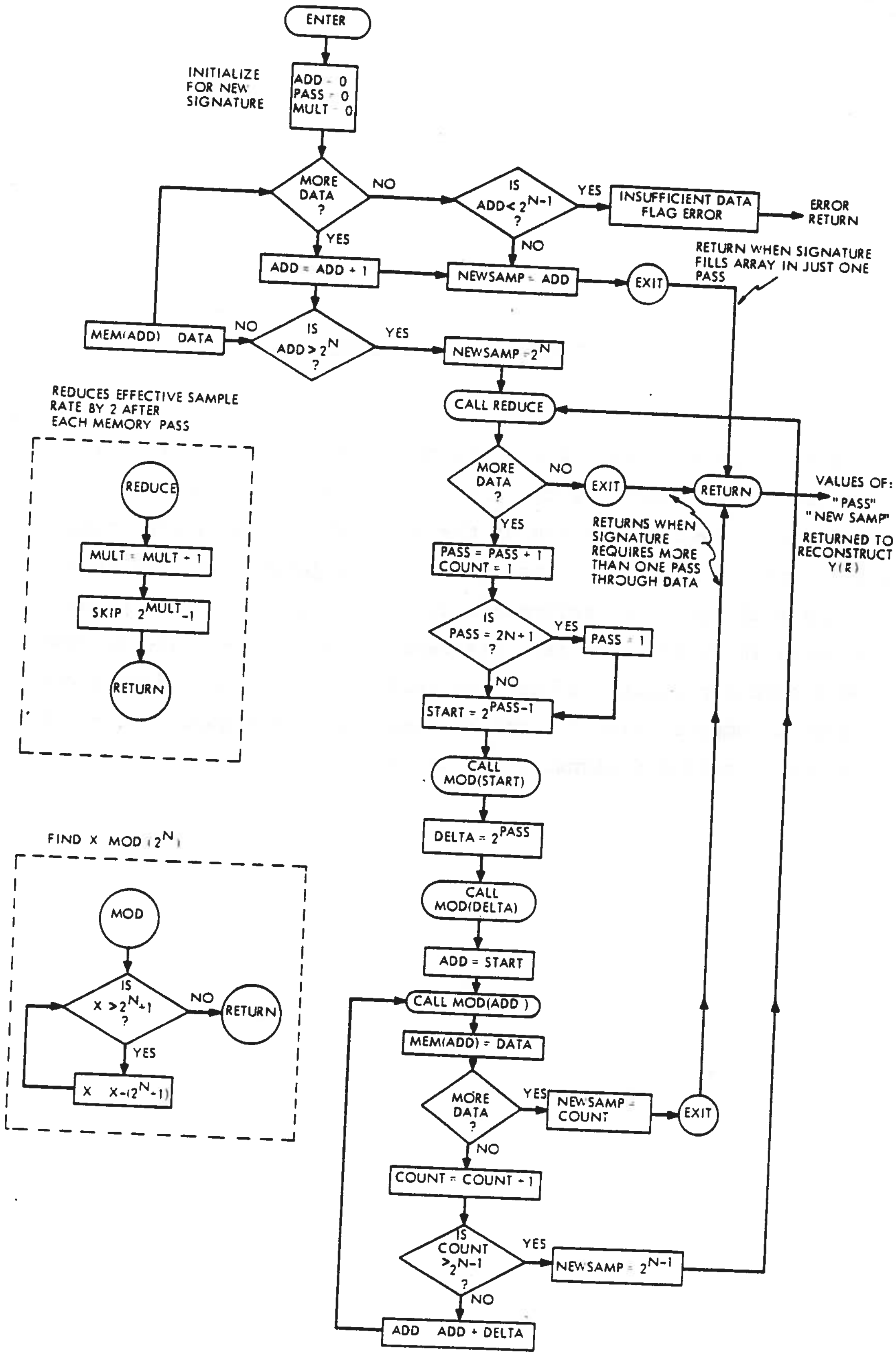


Figure B-2: Phase-Signature Normalization Program