Dynamic Model-Based Techniques for the Detection of Incidents on Freeways

ALAN S. WILLSKY, MEMBER, IEEE, EDWARD Y. CHOW, STUDENT MEMBER, IEEE, STANLEY B. GERSHWIN, MEMBER, IEEE, CHRISTOPHER S. GREENE, MEMBER, IEEE, PAUL K. HOUPT, MEMBER, IEEE, AND ANDREW L. KURKJIAN

***Abstract*—In this paper we discuss an approach to the detection of incidents on freeways. Our techniques are based on the use of a macroscopic dynamic model describing the evolution of spatial-average traffic variables (velocities, flows, and densities) over sections of the freeway. With such a model as a starting point we develop two incident detection algorithms based on the multiple model and generalized likelihood ratio techniques. We also describe a new and very simple system for processing raw data from presence-type vehicle detectors to produce estimates of the aggregate variables, which are then in turn used as the input variables to the incident detection algorithms. Simulation results using a microscopic simulation of a two-lane freeway indicate that 1) our algorithms are robust to the differences between the dynamics of actual traffic and the aggregated dynamics used to design the detection systems; and 2) our methods appear to work as well as existing algorithms in heavy traffic conditions and work better in moderate to light traffic. Areas for future work are outlined at the end of the paper.**

I. MOTIVATION AND OVERVIEW

THE PROBLEM addressed in this paper is the development of a systematic approach to the detection of freeway incidents (accidents, stalled cars, debris on the road, etc.). The goal of our work was the design of algorithms that 1) directly use data from conventional presence detectors which provide binary information at each point in time, indicating the presence or absence of a vehicle directly over the detector; and 2) minimize human operator requirements in detection, classification, and isolation of incident events. The consideration of this problem is of obvious importance both for the efficient dispatching of emergency services and for the design of advanced technology traffic control systems, which require accurate knowledge of existing traffic conditions in order to provide effective on-line control decisions.

Our work represents a new approach to the traffic incident detection problem in that we have based our analysis on a dynamic model that describes the temporal evolution of key traffic variables (flows, densities, velocities) representing aggregate traffic conditions over links of the freeway. Prior to our investigations, several researchers [1]–[8] had studied the problem of reliable incident detection on freeways and had developed a number of automatic detection systems. All of these techniques directly utilize information available from presence detectors. While many of these algorithms take into account the temporal evolution and temporal or spatial correlation of observables derived from detector data, none of these techniques involves the systematic utilization of nonlinear differential equations that relate key traffic variables. In the most comprehensive study of incident detection systems of this type [8], Payne *et al.* have indicated that these techniques have false alarm problems when traffic compression waves occur. Intuitively, the use of dynamic models that capture such phenomena should help to alleviate this problem. In addition, we have found that previously developed algorithms do not do well in detecting capacity-reducing incidents in light or moderate traffic. Again the use of dynamics should be of use in extracting information concerning such incidents in which the direct effect on the observables may not be dramatic.

Motivated by the preceding observations and by the successful studies of dynamic models for traffic behavior [9], [40] and of freeway traffic control based on such models [10]–[13], we have considered the problem of incident detection based on the model proposed by Payne [9], [40], which is reviewed in Section II. Using this model, we have developed incident detection systems using two different hypothesis testing techniques, the multiple model (MM) and generalized likelihood ratio (GLR) algorithms. The MM and GLR methods are briefly reviewed in Section III and IV, and the testing of these algorithms using direct measurements of the aggregate variables is discussed in Section V.

The next step in our study concerned the problem of using presence detector data to produce estimates of the aggregate variables needed as inputs for our detection algorithms. The nature of presence detector data is discussed in Section VI, and in Section VII we develop an extremely simple system for the estimation of traffic variables (specifically, density and flow) from presence detector data. We feel that this system is of interest in itself. In Section VIII we combine this system with our detection algorithms and describe the results of microscopic simula-

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A. S. Willsky, E. Y. Chow, S. B. Gershwin, and A. L. Kurkjian are with the Laboratory for Information and Decision Systems and the Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology, Cambridge, MA 02139.

C. S. Greene is with the Honeywell Systems and Research Center, Minneapolis, MN 53413.

P. K. Houpt is with the Department of Mechanical Engineering, Massachusetts Institute of Technology, Cambridge, MA 02139.

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tions in which presence detector data were generated and used.

The results described in this paper indicate that dynamic model-based detection algorithms do offer the potential for performance improvements over existing algorithms. A number of questions remain to be examined, perhaps the most critical of which is a precise assessment of how much improvement is possible at what cost in terms of increased detection system complexity. Issues such as this and others related to the implementation of MM- or GLR-based incident detection algorithms are presented in Section IX. Because of limitations on space, some of the details of our work have been omitted. The interested reader may find them in [22]–[25], [41].

II. The Aggregate Traffic Model

The detection algorithms we have developed are based on the equations proposed by Payne [9], [40] for the dynamics of freeway traffic flow. This model captures basic aspects of both the fluid flow and car-following models of traffic dynamics. The variables in the dynamic model are spatial mean velocities (v, in mi/h), densities (ρ, in cars/mi/lane), and flows (ϕ, in cars/h/lane) over links of the freeway between presence detector locations. This yields a spatially discretized set of coupled equations,

$$\frac{d\rho_i}{dt}=\frac{\phi_{i-1}-\phi_i}{\delta x_i} \tag{2.1}$$

$$\frac{dv_i}{dt}=-\frac{v_i(v_i-v_{i-1})}{\frac{1}{2}(\delta x_i+\delta x_{i-1})}+\frac{v_i^e(\rho_i)-v_i+\omega_i}{T}-\frac{\nu}{T}\frac{1}{\rho_i}\left[\frac{\rho_{i+1}-\rho_i}{\frac{1}{2}(\delta x_i+\delta x_{i+1})}\right] \tag{2.2}$$

where $\phi_i=v_i\rho_i$. Here subscripts are used to denote the link number with which each variable is associated, δx_i is the length of link i, ω_i represents acceleration noise (used to model normal variations in velocities due to the statistical behavior of individual drivers), and ν and T are parameters introduced by Isaksen and Payne to model driver response characteristics. The $v^e(\rho)$ term represents the driver's desired equilibrium speed as a function of the density of traffic. A number of shapes for this curve have been proposed, and we have used a form which yields the correct properties at high and low density and yields reasonable maximum capacities. Our techniques could be easily adapted to any other choice for the v^e curve. The general form of our v^e curve depicted in Fig. 1, is determined by three free parameters; v_{free} is the equilibrium velocity under light traffic conditions; ρ_{free} is the density at which the equilibrium velocity begins to decrease; and ρ_{jam} is the maximum density of cars that the freeway can hold. The curve between ρ_{free} and ρ_{jam} is logarithmic,

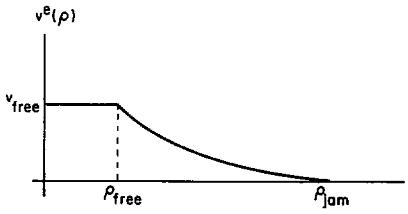

Fig. 1. The v^e curve used.

$$v^e(\rho)=\frac{v_{\text{free}}\ln[\rho_{\text{jam}}/\rho]}{\ln[\rho_{\text{jam}}/\rho_{\text{free}}]}\qquad \rho_{\text{free}}\leqslant\rho\leqslant\rho_{\text{jam}}. \tag{2.3}$$

As we will discuss in a moment, the parameters of the v^e curve can be adjusted on each link [thus the notation v_i^e in (2.2)] to reflect freeway conditions on that link.

Assuming we are modeling M links of the freeway ($i=1$ is the upstream link, $i=M$ is the downstream link), we must modify (2.1), (2.2) on the end links to account for boundary conditions. Specifically, on link 1 we use the equations

$$\frac{d\rho_1}{dt}=\frac{\text{flow}-v_1\rho_1}{\delta x_1} \tag{2.4}$$

$$\frac{dv_1}{dt}=\frac{v^e(\rho_1)-v_1}{T}-\frac{\nu}{T}\frac{1}{\rho_1}\left[\frac{\rho_2-\rho_1}{\frac{1}{2}(\delta x_1+\delta x_2)}\right]. \tag{2.5}$$

For our simulations, "flow" was assumed to be a Poisson arrival process with a specified mean value, which was used to control the overall level of traffic. For link M, we assume a zero density gradient across the last boundary, leading to the equation

$$\frac{dv_M}{dt}=\frac{v_M(v_M-v_{M-1})}{\frac{1}{2}(\delta x_{M-1}+\delta x_M)}+\frac{v^e(\rho_M)-v_M+\omega_M}{T}. \tag{2.6}$$

Links 1 and M essentially establish the boundary conditions, and thus our primary concern is with results on the $M-2$ internal links.

Note that the specification of $v^e(\rho)$ implicitly defines the capacity as the maximum allowable steady-state flow on the freeway. Specifically, using this definition

$$\phi^e(\rho)=\rho v^e(\rho) \tag{2.7}$$

we obtain the "fundamental diagram of traffic" depicted in Fig. 2. From this curve, we see that by adjusting v_{free} or ρ_{free} we can parameterize the capacity (as defined above) on each link of the freeway. Some algebra yields capacity as a function of the parameters,

$$\text{capacity}=\frac{\rho_{\text{jam}}v_{\text{free}}}{e\ln(\rho_{\text{free}}/\rho_{\text{jam}})}$$

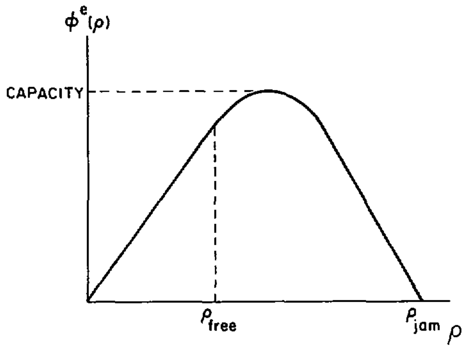

Fig. 2. The fundamental diagram of traffic.

Having this basic model, one can then consider the modeling of abrupt changes in the model that correspond to particular incidents or other inhomogeneities and problems that one wishes to distinguish from capacity-reducing events. Specifically, we have modeled three types of events for each link of the freeway.

1) A capacity-reducing incident on link i. This was modeled as a decrease in the size of ρ_{free} on the ith link, leading to the appropriate decrease in capacity.

2) A pulse of traffic, lasting for a specified duration, entering link i. This model, effected by adding an input to the $\dot{\rho}_i$-equation (2.1), was included for two reasons. First, one may want to detect large disturbances caused by, say, a sporting event letting out, in order to adjust a freeway control algorithm. Secondly, and most importantly, normal random fluctuations of traffic are a possible cause of false alarms for an incident detection system (e.g., the compression wave problems discussed in Section I), and our inclusion of this pulse model was based on a desire to determine if our detection methods were capable of distinguishing such events from real incidents.

3) Sensor failures. As mentioned in Section I, the macroscopic model-based detection systems we have developed assume that one has measurements of ρ_i and v_i on each link. At this level, a sensor failure is defined as any condition such that the sensed density or velocity differs systematically from the actual value of the variable being measured. We will say more about sensor failure models when we discuss the MM and GLR methods in the next two sections.

For our simulation studies, we have considered a six-link freeway, where, under normal conditions, each link was assumed to have the same number of lanes. The parameters ρ_{free} and v_{free} were set at 23.1 cars/mi/lane and 55 mi/h which corresponds to a capacity of 2000 cars/h/lane. The variable FLOW was taken as a mean flow (which was varied in our study) plus a zero-mean fluctuation with a standard deviation of 50 (cars/h/lane). In our initial macroscopic simulation of the MM and GLR detection algorithms we used a reduction of capacity by 1/3 (from 2000 to 1333 cars/h/lane) to model an incident causing the loss of one lane on a three-lane highway. This corresponds to a reduction in ρ_{free} to 7.4. However, our later tests with microscopic simulations led us to modify this model, since an incident in one lane *does* affect traffic in other lanes through the lateral lane switching of vehicles away from the lane on which the incident occurred. The value of ρ_{free} finally chosen was 0.03 cars/mi/lane. This value translates into a capacity of 500 cars/mi/lane—a reduction of 75 percent of capacity.

For the pulse of traffic model on link i, a value of 1600 cars/h/lane was used as an input flow to the density equation on link i. Finally, we have assumed that our measurements of ρ_i and v_i are corrupted by white noise. Initially for the macroscopic studies, the standard deviations of these noises were taken to be 3.33 cars/mi/lane and 5 mi/h, respectively. Later microsimulations, directly using presence detector data, led to larger values for these noises: 10 cars/mi/lane and 28 mi/h (see Section VII).

Finally, both the MM and GLR methods require the use of state estimation techniques. As the dynamics of traffic (2.1), (2.2) are highly nonlinear, an approximate filtering technique has been used. Let our state be denoted by $x(t)$,

$$x'(t)=\left[\rho_1(t),v_1(t),\cdots,\rho_M(t),v_M(t)\right] \tag{2.8}$$

and our measurement vector by $z(t_k)$,

$$z(t_k)=x(t_k)+N(t_k) \tag{2.9}$$

where the components of N are assumed to be independent white noise processes.

The estimation technique we have used is the nominal linearized Kalman filter. Let $\hat{x}(t|t_k)$ be our estimate of $x(t)$ given $Z_k \triangleq \{z(t_1),\cdots,z(t_k)\}$. Then, given $\hat{x}(t_k|t_k)$, we predict ahead to obtain $\hat{x}(t_{k+1}|t_k)$ by integrating (2.1), (2.2) assuming zero noise and an initial condition of $\hat{x}(t_k|t_k)$. The new measurement $z(t_{k+1})$ is then incorporated according to

$$\hat{x}(t_{k+1}|t_{k+1})=\hat{x}(t_{k+1}|t_k)+H\left[z(t_{k+1})-\hat{x}(t_{k+1}|t_k)\right] \tag{2.10}$$

where the gain H is determined off-line by solving for the Kalman filter gain for the traffic model linearized about some equilibrium mean flow-density-velocity point. This linearization has been done about many operating points. Comparing the Kalman gains from a wide variety of such points revealed very little variation with flow. Thus, it appears that one set of gains adequately handles most levels of flow.

III. The Multiple Model Method

The multiple model (MM) method for system identification has been considered by several researchers, and we refer the reader to [26]–[28] and the references cited therein for a detailed development of the technique. The method addresses the problem of identifying a linear-

Gaussian system

$$\dot{x}(t)=Ax(t)+w(t) \tag{3.1}$$

$$z(t_k)=Cx(t_k)+v(t_k) \tag{3.2}$$

given the measurements Z_k and a set of hypothesized models $(i=1,\cdots,N)$

$$\dot{x}_i(t)=A_ix_i(t)+w_i(t) \tag{3.3}$$

$$z(t_k)=C_ix_i(t_k)+v_i(t_k). \tag{3.4}$$

The output of the MM method is the set $p_i(t_k)$ of conditional probabilities for the validity of each of the models given Z_k. A Kalman filter is implemented for each of the N models and the measurement residuals

$$\gamma_i(t_{k+1})=z(t_{k+1})-C_i\hat{x}_i(t_{k+1}|t_k) \tag{3.5}$$

from each filter are used to update the $p_i(t_k)$ according to the equation

$$p_i(t_{k+1})=\frac{F_i(\gamma_i(t_{k+1}))p_i(t_k)}{\sum_{j=1}^{N}F_j(\gamma_j(t_{k+1}))p_j(t_k)} \tag{3.6}$$

where F_i is the probability density for $\gamma_i(t_{k+1})$ assuming the ith model is correct. If hypothesis i is true, then γ_i is a white zero-mean Gaussian sequence with covariance

$$E[\gamma_i(t_k)\gamma_i(t_k)']=V_i(t_k) \tag{3.7}$$

which can be determined off-line as part of the Kalman filter calculations. Thus,

$$F_i(\gamma_i(t_{k+1}))=\frac{\exp\left\{-\frac{1}{2}\gamma_i(t_{k+1})'V_i^{-1}(t_{k+1})\gamma_i(t_{k+1})\right\}}{\left[(2\pi)^m\det(V_i(t_{k+1}))\right]^{1/2}} \tag{3.8}$$

where $m=\dim\gamma_i$.

The MM method has been adapted for use with the Payne model as described in the preceding section. A number of comments need to be made about this design and about the MM method in general.

1) We have implemented a nominal-linearized Kalman filter[1] for each of our hypotheses.

a) For the normal model, the dynamics (2.1), (2.2) used the normal v^e curve on each link.

b) For the model representing an incident on link i, the dynamics (2.1), (2.2) are modified by replacing the normal v^e curve on link i with the reduced capacity curve.

c) For the model representing a pulse of traffic on link i, the dynamics (2.1), (2.2) are modified by including an input flow in the equation for $\dot{\rho}_i$.

2) In addition to the above, there are also a set of models and associated filters representing sensor failures. We have modeled a failure in our ability to measure a particular state variable by modifying the measurement equation (2.9),

$$z(t_k)=Cx(t_k)+N(t_k) \tag{3.9}$$

where C is diagonal, with 1's along the diagonal except for a zero in the location corresponding to the particular state measurement which is hypothesized to be faulty. Note that (3.9) corresponds to modeling a failure as a measurement that contains only noise and is uncorrelated with the state.

3) The residuals from the Kalman filters are used together with (3.6) to compute the probabilities for each hypothesis. Note that (3.6) was derived assuming that:

a) the actual system and all of the hypotheses are linear-Gaussian;

b) one of the hypotheses matches the true system; and

c) the true system does not switch from one hypothesis to another (corresponding, for example, to the onset of an incident).

None of these assumptions is valid, and thus some comments are in order. Assumption 3a) essentially addresses the problem of the utility of the nominal-linearized Kalman filter, i.e., assuming the dynamic model is correct, is it valid to postulate that the filter residuals will be zero-mean, white, with precomputed covariance? The second assumption implies that [under assumption 3a)] the residuals from one of the filters will be white and zero mean. In practice this is never precisely the case, but our experience has been that neither of these assumption has caused great problems. A number of explanations can be given to account for this, but there are no general results that predict when these filters will work well. Based on our experience it is our feeling, however, that, while the estimates from the filters may be sensitive to linearization and model uncertainties, a discrete decision process based on the filter residuals should work well, as long as the models for the several hypotheses are sufficiently different. Intuitively, this can be thought of as a signal-to-noise ratio problem, where the effects of the assumptions add uncertainty. In this sense, assumptions 3a) and b) will limit the minimum size incident that can be detected, where size is to be interpresented as the magnitude of the effect of the incident on the dynamics. For example, we may be able to detect a stalled car, which causes severe and localized capacity reduction, but the smaller effect caused, say, by debris on the road may not be detectable. Also, as we will see, the effect of an incident increases in magnitude as the level of traffic increases. Thus, one might expect there to be a minimum flow level, such that it is impossible to detect incidents in traffic lighter than that level.

Assumption 3c) can lead to difficulties in the ability of MM to detect incidents as they occur, i.e., before the occurrence of an incident on link i, the probability for this hypothesis may become so small that the system will not be able to respond quickly after the incident has occurred. The remedy employed in our work is a relatively common one—a lower bound is set on any probability (we have

[1]From now on we will call all our filters "Kalman filters." It should be understood that they are all nominal linearized Kalman filters.

used 0.01). As we will see, this leads to good response characteristics. We note also that the Kalman filter based on a pulse of traffic on link i is unstable if no such pulse is there (the Kalman filter has a constant driving term in the $\dot{\rho}_i$ equation not present in the true system). Thus, if such a pulse were to develop at some point in time, the filter estimate for this hypothesis might already be so much in error that the MM system might not detect the pulse. To overcome this, whenever the probability of a pulse model falls below 0.05, the estimate produced by this filter is reset to the estimate for the most probable model.

IV. The Generalized Likelihood Ratio Method

The generalized likelihood ratio (GLR) method for detecting abrupt changes in dynamic systems is described in [17] for a specific case and in [30] for a larger class of problems. The basic idea is the following. We assume that a dynamic system under normal conditions is described by the model

$$\dot{x}(t)=Ax(t)+w(t) \tag{4.1}$$

$$z(t_k)=Cx(t_k)+v(t_k). \tag{4.2}$$

A Kalman filter based on this model is implemented. We then hypothesize that an abrupt change (the ith of, say, N possible abrupt changes) in the system occurs at time θ and that this change can modeled by an additive term in (4.1) or (4.2). In this case linearity yields the following model for the residuals of the normal model filter:

$$\gamma(t)=\alpha g_i(t,\theta)+\tilde{\gamma}(t) \tag{4.3}$$

where $\tilde{\gamma}(t)$ is the normal zero-mean white residual and $g_i(t,\theta)$ is the precomputable deterministic *signature* describing the bias induced in γ at time t by a type i abrupt change occurring at time θ. The parameter α is an unknown scalar magnitude for the abrupt change (e.g., the size of a bias in a sensor, the effect of a stalled car on the residuals, which, as we have stated, may depend on the flow level).

Given the model (4.3) for each of the N hypotheses, we compute a set of correlations of the actual filter residuals with the various signatures

$$d_i(t_k,\theta)=\sum_{m=1}^{k} g_i'(t_m,\theta)V^{-1}(t_m)\gamma(t_m). \tag{4.4}$$

The generalized log-likelihood ratio for a type i incident occurring at time θ then is

$$l_i(t_k,\theta)=\frac{d_i^2(t_k,\theta)}{S_i(t_k,\theta)} \tag{4.5}$$

where

$$S_i(t_k,\theta)=\sum_{m=1}^{k} g_i'(t_m,\theta)V^{-1}(t_m)g(t_m,\theta)$$

which can be precomputed. If we define

$$l_i(t_k)=\max_{\theta} l_i(t_k,\theta) \tag{4.6}$$

we then have a measure of the likelihood that a type i incident has occurred sometime in the past.

The GLR algorithm as described above has been adapted for use with the Payne model. Again a number of comments are in order.

1) In this case we have implemented a single nominal-linearized Kalman filter based on the normal dynamics (2.1), (2.2).

2) Since the true system and the Kalman filter are nonlinear, in principle the decomposition of the filter residuals as in (4.3) is not valid. However, we assume a decomposition of this form and thus must calculate the incident signatures, which correspond to the deterministic response to an incident of the true system-normal mode filter combination. The nonlinearity of the system and filter necessitated the computation of these signatures via simulations: the macroscopic model and normal model Kalman filter were simulated without any stochastic effects in the dynamics or measurements, and, for each incident type, the model (2.1), (2.2) was chosen to correspond to the particular incident (e.g., a reduced capacity v^e curve on link i for the link i incident hypothesis). The resulting filter residuals constituted the signature for that incident type. The models used for capacity reducing incidents and traffic pulses were the same as those used in the MM method. Sensor failures, however, were modeled by the development of a bias in one component of z

$$z(t_k)=x(t_k)+N(t_k)+\alpha e_i\sigma(t_k,\theta) \tag{4.7}$$

where α is the unknown bias size, θ is the time at which the failure occurs, e_i is the ith standard basis vector, and $\sigma(t,\theta)$ is the unit step ($=0$ for $t<\theta$, $=1$ for $t\geq\theta$).

3) As with the MM algorithm, the GLR system is based on several assumptions that do not hold in the application to incident detection. For example, modeling errors imply that none of the hypotheses is precisely correct. As we discussed in the preceding section, the issue then becomes one of whether the effect of the incident on the observables is significantly larger than the effect of the approximations and uncertainties.

4) Note that, unlike the MM algorithm, the GLR method explicitly considers the shifting of the system from normal to incident conditions at an unknown time. In principle we should calculate $l_i(t_k,\theta)$ for $\theta=t_1,\cdots,t_k$— a growing computational load. We have employed a standard method for overcoming this—we compute l_i only for a "sliding window" of the most recent past, $t_{k-M}\leq\theta\leq t_k$. With a sampling time $t_k-t_{k-1}=5$ s, we have kept a 250 s window (51 points).

V. Simulations of the Macroscopic Detection Systems

The first two sets of tests of the GLR and MM systems were designed to determine the performance characteristics of these methods and their robustness in the presence of both modeling errors and the effects of the linearizations involved in their design. For each of these sets of

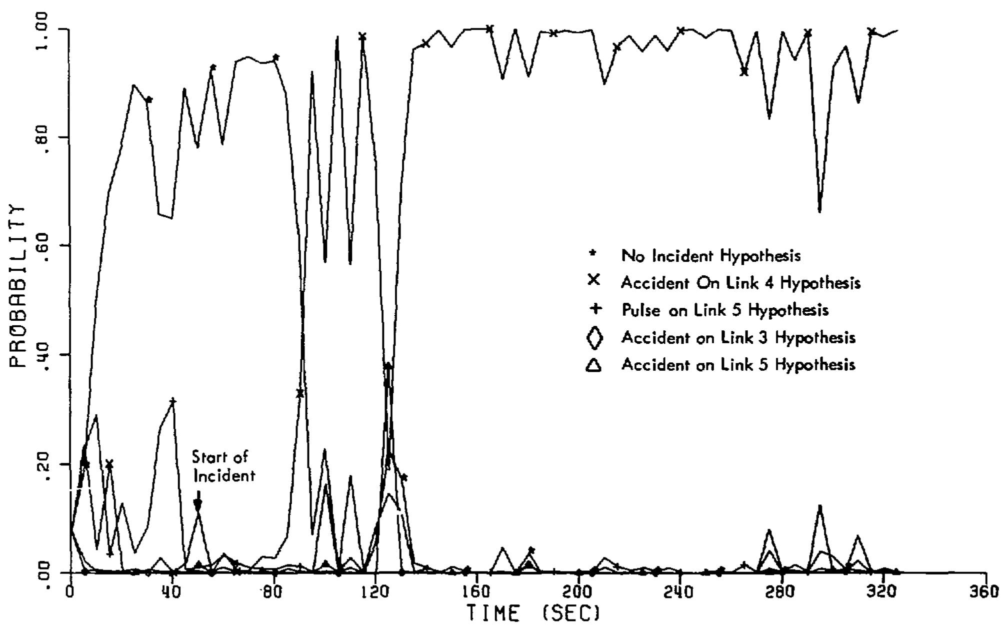

Fig. 3. MM probability plot. Accident on link 4, nominal flow = 1000 cars/h/lane; aggregate model simulation.

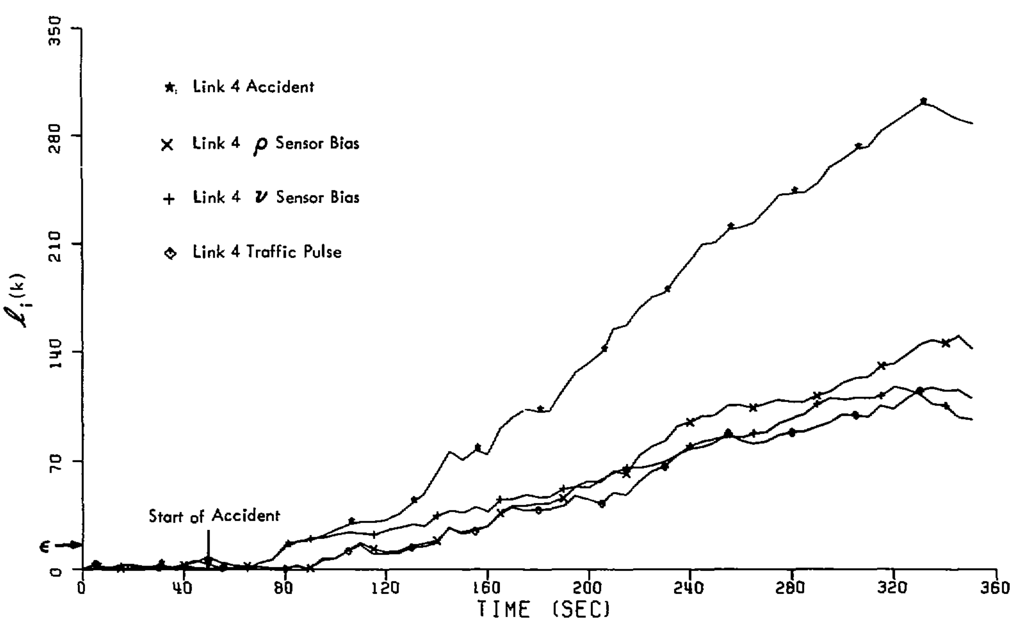

Fig. 4. GLR, $l_i(k)$: Link 4 accident; nominal flow = 1000 cars/h/lane; aggregate model simulation.

tests, the GLR and MM systems were designed about a single, fixed operating point with fixed values for all parameters, such as the assumed measurement noise covariances, the postulated effects of different incidents on traffic dynamics, etc. The parameter values used were those given in Section II. In addition, the linearized Kalman filters were designed about a high mean flow operating point of 1667 cars/h/lane.[2]

The first set of tests involved the use of data obtained from simulating the model (2.1), (2.2) using parameter values that differed from those assumed in the MM and GLR designs. The parameters that were varied are as follows.

[2]Note that this mean flow not only affects the gain, but it also is a driving term in the prediction step of the filters, as it enters in as a driving term in the equation for $\dot{\rho}_1$.

1) The actual mean flow onto link 1. This was varied from a low flow of 900 cars/h/lane up to capacity (2000 cars/h/lane).

2) The sensor noise variances. Significantly larger values for these variances were used in some of the experiments.

3) The initial estimation error. Large values were used for this in order to observe the transient behavior of the algorithms.

The performance of both systems was encouraging.

1) Detection performance was uniformly good over the entire range of actual mean flows used (900–2000 cars/h/lane). No false alarms were observed, no incorrect detections (e.g., declaring a pulse on link 3 when the true event was an incident on link 4) occurred, and the response time of the systems was small. Figs. 3 and 4

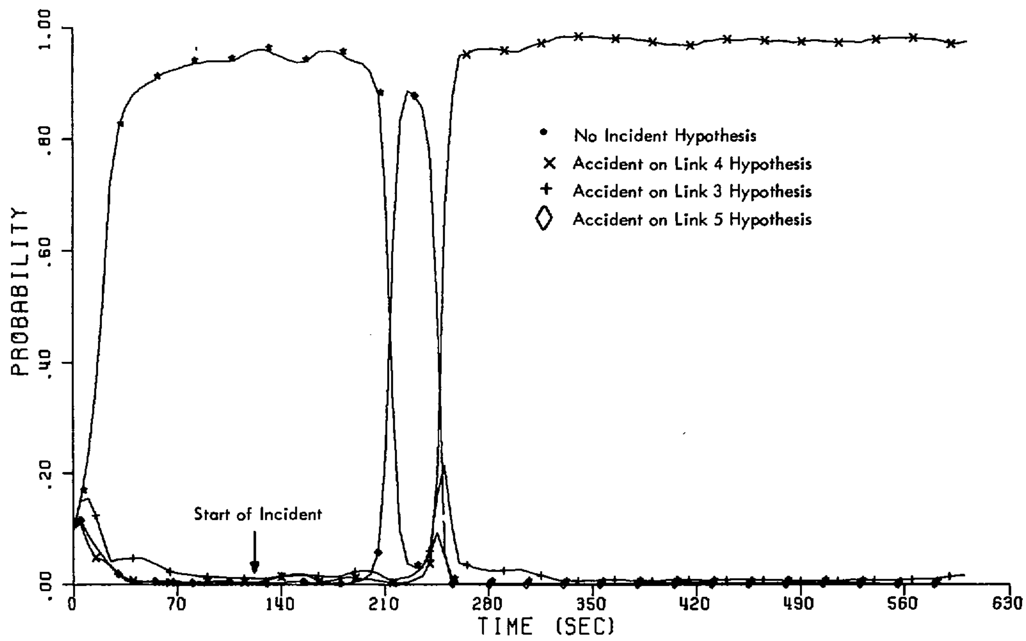

Fig. 5. MM probability plot. Accident on link 4; nominal flow=1000 cars/h/lane; aggregate measurements from microscopic simulation.

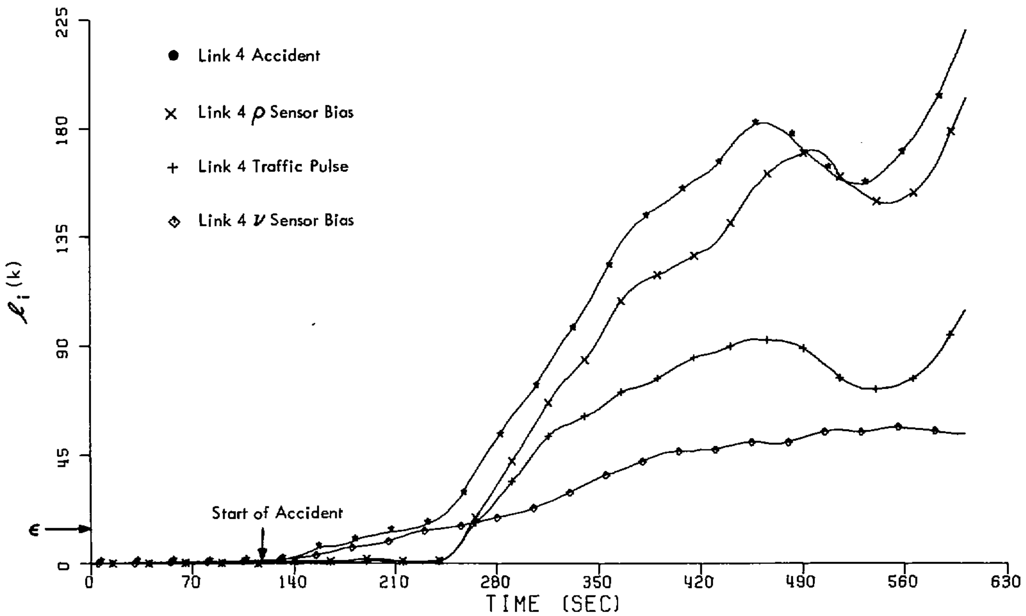

Fig. 6. GLR, $l_i(k)$: Accident on link 4; nominal flow=1000 cars/h/lane; aggregate measurements from microscopic simulation.

illustrate typical performance of the GLR and MM systems. The value of ϵ indicated in Fig. 4 and in later figures is 16. Under all of the assumptions used in the derivation of the GLR method (such as the whiteness of the residuals), this threshold implies a false alarm probability at any instant of time of less than 0.0002.

2) Performance is somewhat degraded when the actual measurement variances are a factor of 16 larger than nominal. All incidents were correctly identified with, however, increased detection delay.

3) Large initial estimation errors cause only transient effects on GLR and MM. Performance is excellent after the initial startup.

These tests, while indicating a certain level of robustness of the GLR and MM systems, do not provide information about system robustness to the details of the Payne model. To provide this type of information, we have used a microscopic traffic simulation [15]. This program is based on the St. John car-following equations [14] and can be used to simulate traffic under almost any conditions. The program simulates two lanes of flow, operates in discrete time, and offers the following features:

a) a variety of vehicle and driver types can be modeled,

b) presence detectors can be placed as desired,

c) on-ramp and input flow rates can be specified,

d) accidents can be simulated by stopping a vehicle at any desired time and location.

Because the simulation is based on a microscopic model, the position, speed, acceleration, driver type, and

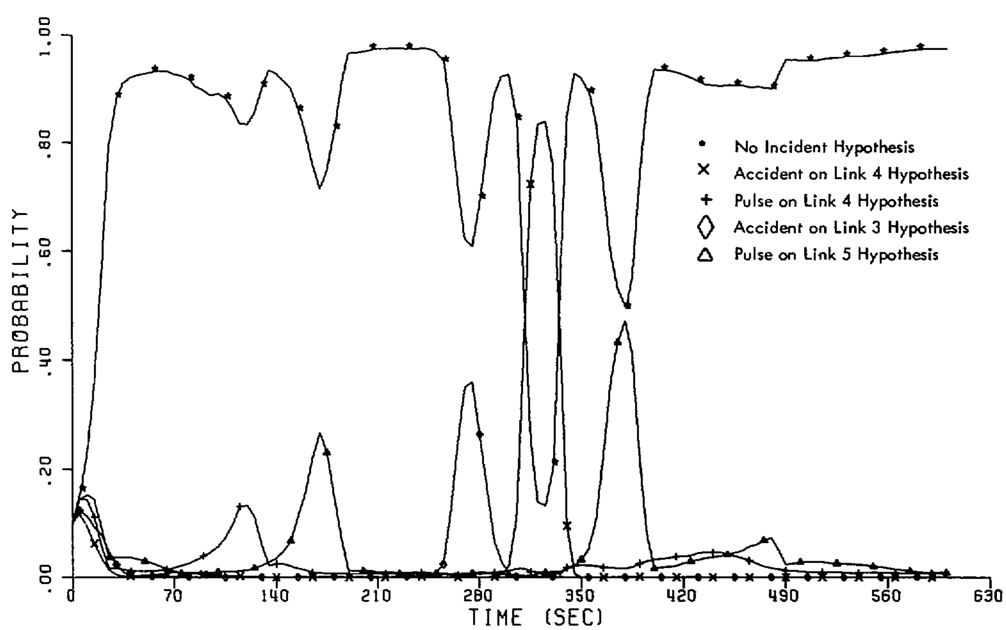

Fig. 7. MM probability plot. No accident, two slowly moving vehicles; nominal flow = 1000 cars/h/lane; aggregate measurements from microscopic simulation.

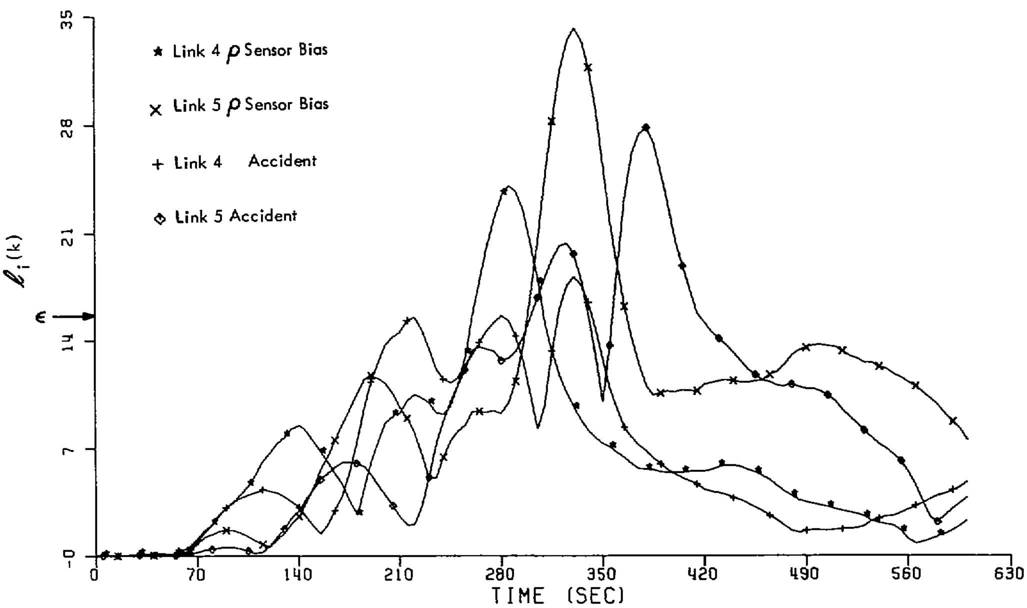

Fig. 8. GLR, $l_i(k)$: No accident, two slowly moving vehicles; nominal flow = 1600 cars/h/lane; aggregate measurements from microscopic simulation.

vehicle type for each vehicle on the road are known and available in the program. Thus, it is possible to compute the density and average velocity of traffic over links of the simulated freeway. We have done this in order to generate measurements (which we have then corrupted with noise) of the aggregate variables used in the GLR and MM algorithms. These data were then fed into the detection systems. The following are the conclusions that can be drawn from this study.

1) Both the GLR and MM systems performed well in detecting incidents down to flow levels of 900 cars/h/lane. This gives us an idea of the fundamental limitations of our algorithms—at flows less than this the various noise sources and approximations are stronger than the "signal" due to the incident.

2) The GLR approach has some difficulties at low flows in distinguishing incidents from sensor biases. We will discuss this problem in Section IX. See Figs. 5 and 6 for typical MM and GLR responses.

3) Short-term spatial inhomogeneities in traffic cause transient responses in the GLR and MM systems. Figs. 7 and 8 are from a simulation in which two slowly moving vehicles disrupt traffic flow. As expected, this looks like a "traveling incident." This could be alleviated by a persistence requirement on the probabilities or log-likelihood or by incorporating a traveling incident model for MM and signature for GLR.

Thus, while some questions are raised by these simulations, the basic conclusion of this study is that the MM and GLR algorithms appear to be insensitive to the details of the dynamic models used in their design and to the precise parameter values used. On the other hand, the measurements used by the MM and GLR algorithms in these simulations are not available in practice: in the first set we used a macroscopic simulation, while in the second we used a microscopic simulation and actually computed the aggregate variable measurements needed by counting cars on each link and averaging their velocities. What is still missing is a system for taking presence detector data and producing estimates of ρ_i and v_i that can then be used as inputs to the GLR and MM systems. This is the topic of the next few sections.

VI. The Nature of Presence Detector Data

In this section we briefly discuss the type of information contained in the outputs of presence detectors. A detailed discussion is contained in [23]. The ideal output of a detector at any time is 0 if no car is above the detector and 1 if a car is present. Hence, the time history of a detector output is a sequence of unit pulses, whose pulsewidth is the time that an individual car is over the detector. From such data, one can directly compute two quantities of importance in estimating aggregate traffic variables and in detecting incidents.

1) Car count data—the number of cars passing a given detector station in a prescribed interval of time. This directly yields flow information, i.e., cars/h/lane.

2) Occupancy data—the percentage of time that cars are over the given detector during the prescribed time interval. This is related to traffic density.

Intuitively, when a capacity reducing blockage occurs somewhere on a freeway, the density of traffic upstream of the incident location increases, while it decreases downstream. Hence, one can consider designing incident detection algorithms that look for low occupancy at the downstream detector and high occupancy at the upstream detector. In fact, this is the basis of many of the algorithms discussed [1]–[8]. One particular algorithm of this type, the so-called Algorithm #7, has emerged as the most widely accepted incident detection system [8]. This algorithm employs an occupancy difference test along the lines of the one mentioned above, together with a persistence requirement (to reduce false alarms) and a test at adjacent detectors to reduce the number of alarms caused by traveling compression waves. The details of this algorithm are described in [8] and in [23].

We have used our microscopic simulation, equipped with presence detectors at half-mile intervals to generate a number of scenarios for the testing of Algorithm #7 and of the systems described in the next two sections. These results indicate that Algorithm #7 detects incidents well in heavy traffic but has difficulty in detecting incidents in low or moderate traffic. In our simulations this algorithm was unable to detect incidents in flows below 1400 cars/h/lane. In fact, in [23] it is argued that the probability is 0.5 that Algorithm #7 will be able to detect (with arbitrarily large detection delay) an incident at a flow of 1300 cars/h/lane. For the v^e curve described in Section II, this flow corresponds to a high enough density ($>\rho_{\text{free}}$) so that the equilibrium velocity is 48 mi/h. Thus, this is not a light traffic condition.

Although the above comments indicate a limitation to the performance of Algorithm #7, it should be remembered that 1) this algorithm directly uses presence detector outputs and 2) the algorithm is extremely simple to implement. In the next two sections we develop a method for using presence detector data with the MM and GLR systems. In Section IX we discuss the complexity issue.

VII. The Estimation of Aggregate Variables from Presence Detector Data

As described in the preceding section, a presence detector provides time-averaged information about traffic conditions at a *fixed spatial location*. On the other hand, the variables in the models on which the GLR and MM systems are based are spatial-averaged quantities at fixed times. A number of authors [32]–[35] have considered the problem of processing data of the first type to produce estimates of variables of the second kind. The simplest of these is discussed by Nahi and Trivedi [32], [33]. Their recursive estimation system is based upon counting vehicles as they enter and exit the link. Given a good initial density estimate, Nahi's method showed the ability to track the density very closely in spatially homogeneous conditions. In fact, an explicit homogeneity assumption was made in the development of the system. This type of assumption is clearly not valid for incident conditions and can be expected to lead to large estimation errors.

Motivated by the results in [32], [33] we have developed a new link density estimation system that is very simple and also overcomes the limitations of Nahi's system. Consider a single link of a freeway with detectors in each lane at both ends of the link. Let Δ be the time interval over which the temporal averaging of loop detector data is performed, and let k denote the discrete-time index, e.g. $\rho(k)$ denotes the spatial average density at time $k\Delta$. Let

$C_u(k), C_d(k)=$ the number of cars counted in the time interval $(k-1)\Delta \leqslant t \leqslant k\Delta$ at the upstream and downstream detector stations, respectively

$\mathrm{OCC}_u(k), \mathrm{OCC}_d(k)=$ the occupancy measured over the time interval $(k-1)\Delta \leqslant t \leqslant k\Delta$ at the upstream and downstream detector stations, respectively.

First note that $C_u(k)/\Delta$ is a direct measure of the flow (cars per unit time) at the upstream detector, and $C_d(k)/\Delta$ is an analogous measure at the downstream detector. Thus, a reasonable estimate of flow on the link is the average of these quantities,

$$\hat{\phi}(k)=\frac{C_u(k)+C_d(k)}{2\Delta} \tag{7.1}$$

Also note that the difference $C_u(k)-C_d(k)$ measures the change in the number of cars on the link during the time interval $(k-1)\Delta \leqslant t \leqslant k\Delta$. Hence, we directly obtain the following equation for the evolution of link density:

$$\rho(k)-\rho(k-1)=\frac{C_u(k)-C_d(k)}{h}+w(k-1)$$
$$\triangleq u(k-1)+w(k-1) \tag{7.2}$$

where h is the length of the link and $w(k-1)$ is a noise process used to model the possible discrepancies between the actual change in the number of cars on the link and the number obtained from car count information. This discrepancy may be caused by imperfections in the detectors, by a detector missing a car, or by a car being counted by detectors in two different lanes at the same station (see [23], [41] for details). The calculation of the variance Q of $w(k-1)$ is discussed in [23], and a value of Q on the order of 0.1 (cars/mi/lane)^2 was found to be valid over a wide range of traffic conditions.

Equation (7.2) implies that we can use car count data to keep track of *changes* in density, but by itself such data cannot reduce any initial uncertainty in ρ, and the accumulation over time of the noise process $w(k)$ will lead to further deterioration in our estimate of density. Thus, we would like to use occupancy data to provide a direct measurement of density. Intuitively, if traffic is spatially and temporally homogeneous, one should be able to relate temporal averages to spatial averages. Using results of this type [36]–[38], it is shown in [23], [41] that under spatially homogeneous conditions density is proportional to occupancy. Thus, let

$$z(k)=\frac{\mathrm{OCC}_u(k)+\mathrm{OCC}_d(k)}{2\alpha} \tag{7.3}$$

where α is the occupancy-density proportionality constant (see [23], [41] for the evaluation of α). Then, under spatially homogeneous conditions, we have

$$z(k)=\rho(k)+\eta(k) \tag{7.4}$$

where $\eta(k)$ is an unbiased sequence of errors, which are assumed to be white with known variance R. Results in [23] indicate that the variance of $\eta(k)$ should be taken in the range from 50–100 (cars/mi/lane)^2.

Given the model (7.2), (7.4) we can design a one-dimensional Kalman filter as a density estimation system that works well under spatially homogeneous conditions

$$\hat{\rho}(k+1|k)=[1-H]\hat{\rho}(k|k-1)+Hz(k)+u(k) \tag{7.5}$$

where the filter gain and the variance V of the residual $\gamma(k)=z(k)-\hat{\rho}(k|k-1)$ are calculated from the usual Kalman filter equations.

This system has been studied using our microscopic simulation, and, under normal conditions, large initial errors in the estimate of ρ can be reduced significantly within 1 min with measurements taken every 5 s. This is a major improvement over previously developed techniques.

Recall that the underlying assumption behind (7.4) is the homogeneity of traffic. Clearly, any inhomogeneity, such as an incident, may cause the relationship (7.4) to fail. This leads directly to the idea of monitoring the residuals $\gamma(k)$ in order to *detect* and compensate for such inhomogeneities. To this end, we consider a simple model for the development of spatial inhomogeneities—the onset of a bias of unknown size ν,

$$z(k)=\rho(k)+\eta(k)+\nu\sigma(k-\theta) \tag{7.6}$$

(where $\sigma(m)=1,\ m\geqslant 0,\ =0,\ m<0$).

Using (7.2), (7.6) we can devise a simple density estimation system for use under *any* traffic conditions. Design a Kalman filter as in (7.5). Then, following the discussion of the GLR algorithm in Section IV, the residuals can be written as

$$\gamma(k)=\nu g(k-\theta)+\tilde{\gamma}(k) \tag{7.7}$$

where $\tilde{\gamma}(k)$ is a zero-mean white process with variance V. The signature $g(k-\theta)$ can be easily calculated in this case as

$$g(j)=(1-H)^j. \tag{7.8}$$

We now can implement a GLR-based algorithm (not to be confused with the incident detection algorithm of Section IV). We compute $d(k,\theta)$, $l(k,\theta)$, and $S(k-\theta)$ using $g(k-\theta)$ as given in (7.13) and the scalar versions of (4.4)–(4.6) (with t_m replaced by m). A sliding window of $k-13\leqslant\theta\leqslant k-9$ was used for these calculations. Then, letting

$$\hat{\theta}(k)=\underset{k-13<\theta<k-9}{\arg\max}\ l(k,\theta) \tag{7.9}$$

the decision rule used was

$$l(k,\hat{\theta}(k)) \underset{\text{normal conditions}}{\overset{\text{bias detected}}{\gtrless}} \epsilon \tag{7.10}$$

where the threshold ϵ is chosen to provide a reasonable tradeoff between false alarms and correct detections. Note that the probability of detection depends upon the size ν of the bias. In [23] a discussion is given of the expected size for ν under different traffic conditions. The results of this analysis are that the size of ν increases with increasing flow. Thus, one can set ϵ at a higher value in heavy traffic, reducing false alarms while maintaining a high correct detection probability. Note that flow-scheduled thresholds are easily implemented, as the estimate of ϕ given by (7.1) is good.

Following the detection of a bias, we want to compensate the filter estimate $\hat{\rho}$ to correct for the effect of the bias. In a manner similar to the calculation of $g(k-\theta)$, we can calculate the bias ρ_b in $\hat{\rho}(k|k)$ caused by a measurement bias ν occurring at time θ,

$$\hat{\rho}_b(k)=\left[1-(1-H)^{k-\theta+1}\right]\triangleq F(k-\theta)\nu. \tag{7.11}$$

Then, given that a detection is made at time k and given the most likely time $\hat{\theta}$ from (7.19) and the most likely

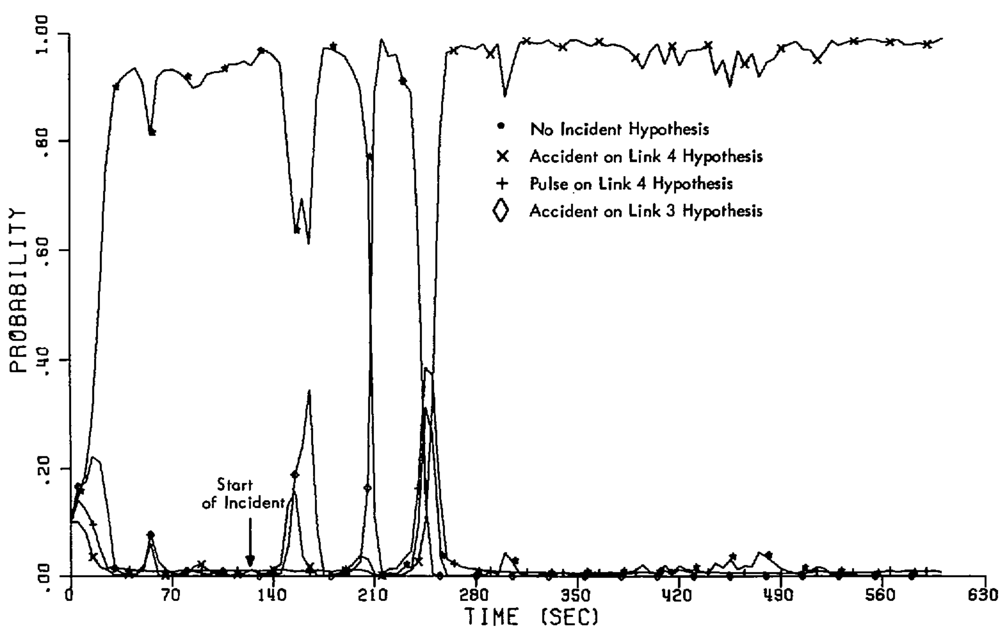

Fig. 9. MM probability plot. Accident on link 4; nominal flow=1000 cars/h/lane; presence detector data.

magnitude of the measurement bias [17]

$$\hat{\nu}=\frac{d(k,\hat{\theta})}{S(k-\hat{\theta})} \tag{7.12}$$

we obtain a correction to the estimate following the detection,

$$\hat{\rho}(k|k)_{\text{new}}=\hat{\rho}(k|k)_{\text{old}}-F(k-\hat{\theta})\hat{\nu}. \tag{7.13}$$

Having done this and having compensated the measurements by subtracting $\hat{\nu}$ from all incoming measurements, we are in a position to detect further changes, such as the return to homogeneous conditions. This system has performed extremely well in all types of inhomogeneous traffic conditions. For a detailed discussion of the performance of this algorithm, see [23], [41].

Finally, recall that the GLR and MM systems require measurements of both ρ and v. We can obtain an estimate of velocity as follows:

$$\hat{v}(k)=\frac{\hat{\phi}(k)}{\hat{\rho}(k|k)}.$$

This estimate is not nearly as good as the estimates of ϕ and ρ, due to the errors in the approximation $v=\phi/\rho$. Note that for a compressible fluid this is an exact relationship if we use point values for v, ϕ, and ρ. It is only approximate if we use spatial averages.

VIII. The GLR and MM Algorithm Using Presence Detector Data

The system described in the preceding section for computing estimates of spatial mean densities and velocities was combined with the GLR and MM algorithms, with the estimates produced by the former being used as the measurements for the latter. This combined system was then tested using the same microscopic simulations as described in Section V, although in this case detector data were used directly. As discussed in Section II, the GLR and MM systems were modified slightly by using larger values for measurement noise variances to account for the errors in the estimates of ρ and v provided by our detector data preprocessing algorithm.

As one might expect the additional errors introduced by the increased uncertainties in our derived measurements of ρ and v lead to a slight increase in the minimum flow at which incidents can be detected. However, these algorithms still detected incidents in flows down to 1000 cars/h/lane. Recall the Algorithm #7 required flows of at least 1400 cars/h/lane in our simulations.

Aside from this increase in minimum flow required for detection, the simulation results using presence detector data are extremely similar to the results obtained using aggregate measurements directly computed from the microsimulation. Compare Figs. 9 and 10 with Figs. 5 and 6.

IX. Discussion

In this paper we have described the application of modern estimation and detection techniques to the problem of detecting incidents on freeways. The algorithms we have developed have shown promise of providing performance improvements over existing algorithms. Moreover, the extremely simple system we have developed for estimating aggregate traffic variables from presence detector data should be of interest in traffic surveillance applications other than incident detection.

While the techniques that we have developed have yielded encouraging results, a number of further questions

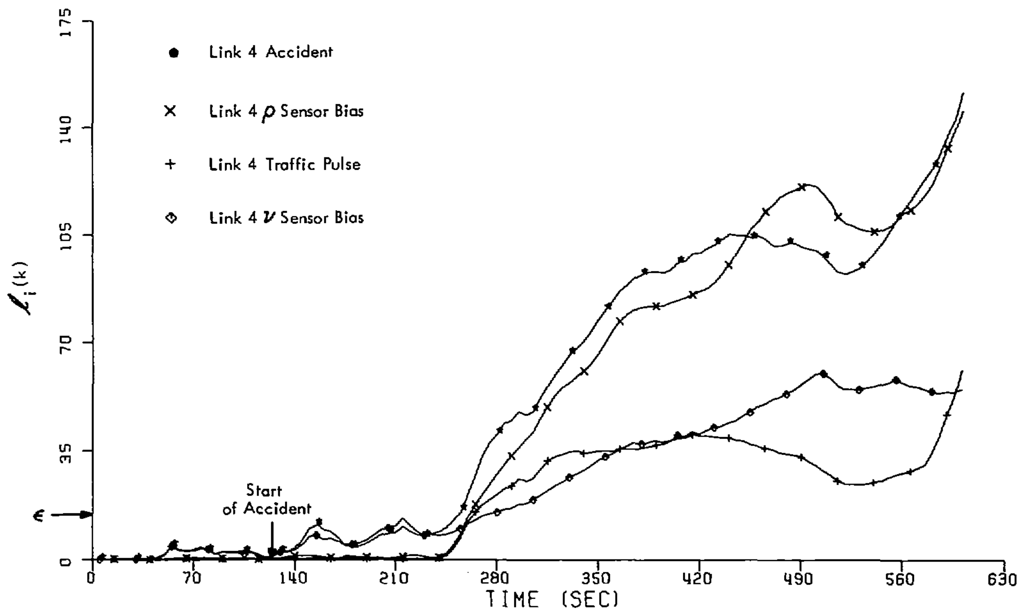

Fig. 10. GLR, $l_i(k)$: same simulation as in Fig. 9.

must be addressed. First, the system described in Section VII provides good estimates of ρ but rather poor ones of v. Several possibilities for improved velocity estimation are discussed in [20], [22], [23]. An alternative to using such a system would be the use of ρ and ϕ as the basic measured variables in the design of the GLR and MM systems. Another problem that must be attacked is that of sensor failures. As discussed in Section V, the GLR technique has some difficulties in distinguishing incident hypotheses and some of the sensor bias models. The main point involved in alleviating this problem is the observation that macroscopic sensor failure models have very little to do with the actual failure of a presence detector. Thus, it seems preferable to perform sensor failure detection directly on the presence detector data. Fail to zero or full-on failures are not difficult to detect using simple logic directly on detector outputs. Also, it is possible to design a GLR system, much as that discussed in Section VII, for the detection of sensor failures.

Work is needed in the development of useful detection rules, based on the MM probabilities or GLR log-likelihood ratios. Persistence requirements (i.e., p_i or l_i remaining above a threshold for a period of time) are clearly needed, and such a feature will eliminate many problems such as the transient response of GLR and MM in the simulation containing two slowly moving vehicles. In addition, we may wish to consider flow-scheduled thresholds, as were used in our aggregate variable estimation system. Here, one could use higher thresholds in high flows to avoid false alarms caused, for example, by compression waves. One would not be sacrificing very much in terms of detection performance, as the effect of an incident in heavy traffic is much larger than in light traffic. Conversely, a lower threshold in light traffic would improve detection performance without any drastic effect on the false alarm rate, since large amplitude spatial inhomogeneities do not occur under normal conditions when traffic is light.

The inclusion of additional hypotheses (and the deletion of some of the present ones) should also be investigated for both the GLR and MM systems. Basically, we should aim to include hypotheses for events that we want to detect plus hypotheses for events, such as slowly moving vehicles, which may confuse the detection algorithms unless accounted for. In addition, the use of more complex dynamic models, incorporating effects such as the lateral motion due to lane changing, should be considered, as such phenomena play a significant role in the dynamics of traffic under incident conditions and consequently offer the possibility of improved signal-to-noise ratio if they are included in our models. Further, at least a simple model of lane changing clearly must be considered if presence detectors are not placed in every lane at every station.

Finally, computational issues in the implementation of the MM and GLR systems must be examined, and the algorithms should be tested on real data in order to provide a basis for deciding if the complexity of these systems is justified by commensurate performance. For an initial discussion of implementation questions for MM and GLR we refer the reader to [22]–[24]. As for the performance of these systems, the results of our simulations using presence detector data generated by a microscopic dynamic model of freeway traffic indicate that the MM and GLR algorithms offer the possibility of improved detection capabilities over existing algorithms. This step is a significant one, as these simulations were *not* based on an aggregate traffic model but on models for individual vehicles. On the other hand, systems such as Algorithm #7 were developed and have been tested on real data, and the real test of the robustness and promise of our techniques will come from similar experiments.

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Alan S. Willsky (S'70–M'73) was born in Newark, NJ, on March 16, 1948. He received the S.B. degree in aeronautics and astronautics and the Ph.D. degree in instrumentation and control from the Massachusetts Institute of Technology, Cambridge, in 1969 and 1973, respectively.

From 1969–1973 he held a Fannie and John Hertz Foundation Fellowship. He joined the faculty of the Department of Electrical Engineering and Computer Science, M.I.T., in 1973 and is presently an Associate Professor of Electrical Engineering and Assistant Director of the M.I.T. Laboratory for Information and Decision Systems. He is also a member of the Board of Directors of Alphatech, Inc. From February–June of 1977 he was a Science Research Council Senior Visiting Fellow at Imperial College, London, England. He is Editor of the M.I.T. Press series of books in signal processing, optimization, and control, and was the program Chairman for the 17th IEEE Conference on Decision and Control held in San Diego, CA, in January 1979.

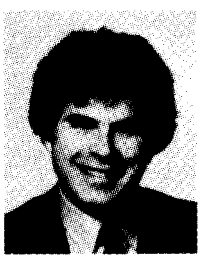
He is the author of one book, *Digital Signal Processing and Control and Estimation Theory: Points of Tangency, Areas of Intersection, and Parallel Directions* (Cambridge, MA: M.I.T. Press, May 1979). The paper "Relationships Between Digital Signal Processing and Control and Estimation Theory" (PROCEEDINGS OF THE IEEE, vol. 66, September 1978), for which he was awarded the 1979 Alfred Noble Prize by the American Society of Civil Engineers and the 1980 Browder J. Thompson Memorial Prize Award by the Institute of Electrical and Electronics Engineers, provides an introduction to many of the topics addressed in the book. He is presently working on an undergraduate text, *Signals and Systems*, coauthored with Prof. A. V. Oppenheim and Dr. I. T. Young, to be published by Prentice-Hall. He has written numerous papers in algebraic system theory, nonlinear filtering, failure detection, stochastic processes, and biomedical signal processing. His present research interests are in problems involving abrupt changes in signals and systems and the related problems of detection and reliability, the modeling and processing of spatially distributed random data, digital signal processing issues in control system design, and the analysis of stochastic processes and systems. In 1975 he received an award from the M.I.T. Graduate Student council for outstanding teaching, and in August 1975 he received the Donald P. Eckman Award from the American Automatic Control Council.

Dr. Willsky is a member of the Society for Industrial and Applied Mathematics, Sigma Xi, Sigma Gamma Tau, and Tau Beta Pi.

Edward Y. Chow (S'77) was born in Hong Kong on August 5, 1952. He received the B.S. and M.S. degrees in electrical engineering from the Massachusetts Institute of Technology, Cambridge, in 1974 and 1976, respectively.

From February 1976 to August 1976, he worked at the C. S. Draper Laboratory in Cambridge, MA. Presently, he is completing his doctoral thesis research on a design methodology for failure detection systems at the M.I.T. Laboratory for Information and Decision Systems. Upon receiving his doctorate, he will join the Schlumberger-Doll Research Center, Ridgefield, CT.

Mr. Chow is a member of Eta Kappa Nu and Tau Beta Pi.



Stanley B. Gershwin (S'69–M'71) was born in Brooklyn, NY, on September 24, 1945. He received the B.S. degree in engineering mathematics from Columbia University, New York, NY, in 1966 and the M.A. and Ph.D. degrees in applied mathematics from Harvard University, Cambridge, MA, in 1967 and 1971, respectively.

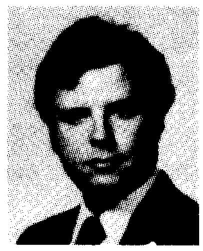
In 1969–1971 he was employed by the Bell Telephone Laboratories, Holmdel, NJ, where he studied a procedure for estimating telephone hardware capacity using very limited data. At the Charles Stark Draper Laboratory in Cambridge, MA, from 1971 to 1975, he studied problems in manufacturing and in transportation. His interests in these areas continues at the M.I.T. Laboratory for Information and Decision Systems, where he has worked since 1975, and is investigating problems in control, optimization, and estimation as well. He has studied perturbations of traffic assignments, the energy consumption in traffic networks with multiple vehicle types, the effects of traffic control on driver behavior, the measurements of traffic flow parameters, the detection of incidents on freeways, and related areas in transportation. He has investigated routing optimization in networks of machine tools and the effects of limited buffer storage space on transfer lines and assembly networks.

Dr. Gershwin is a member of the IEEE Control Systems Society, Tau Beta Pi, the American Association for the Advancement of Science, and the Operations Research Society of America.

Christopher S. Greene (S'68–M'78) was born in Aurora, IL, on March 17, 1950. He received the B.S. degree in electrical engineering from the University of Colorado, Boulder, in 1973 and S.M. and Ph.D. degrees in electrical engineering from the Massachusetts Institute of Technology, Cambridge, in 1975 and 1978, respectively.

From 1973–1978 he held various teaching and research assistantships at M.I.T. doing research in the areas of adaptive control and decision making. Since 1978, he has been a Research Engineer at Honeywell's Systems and Research Center in Minneapolis, MN, doing research on the control of large flexible spacecraft.

Dr. Greene is a member of Sigma Xi and the American Institute of Aeronautics and Astronautics.



Paul K. Houpt (M'67) was born in Washington, DC, in 1944. He received the B.S. degree from Syracuse University, Syracuse, NY, in 1966, the M.S. degree from New York University, New York, NY, in 1968, and the Ph.D. degree from the Massachusetts Institute of Technology, Cambridge, in 1974, all in electrical engineering.

From 1966–1970, he was with the Electronic Power Systems Division, Bell Laboratories, Whippany, NJ. In 1974 he joined the staff of the M.I.T. Laboratory for Information and Decision Systems (formerly Electronic Systems Laboratory) where he held the position of Research Associate until 1978; during that period his research interests focused on the application of optimal control and estimation theory to urban vehicular traffic control and automated rapid transit. Since 1979 he has been with the Department of Mechanical Engineering, M.I.T., where he is presently an Assistant Professor. His current research interests include modeling and control of internal combustion engines, control of automated vehicular transportation systems, and fundamental studies of architecture and algorithms for direct digital control. He has served as a consultant to Artisan Industries Corp., Waltham, MA, FIAT, Central Research, Turin, Italy, Computer Controls Corp., Wilmington, MA, and Wind Turbine Generators (WTG), Inc., Buffalo, NY.

Andrew L. Kurkjian was born in Washington, DC, on January 13, 1953. He received the B.S. degree in electrical engineering from the Catholic University of America, Washington, DC, in 1975 and the M.S. and E.E. degrees in electrical engineering from the Massachusetts Institute of Technology, Cambridge, in 1978.

He is currently completing his Ph.D. degree in electrical engineering at M.I.T. His current research is in the areas of digital signal processing and acoustic wave propagation with applications to sonic well logging.

Mr. Kurkjian is a member of Sigma Xi and Tau Beta Pi.