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Estimation of Traffic Situation and Incident Detection on Freeway Network by Filtering Technique

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1. INTRODUCTION

The problem of monitoring traffic flow from isolated detectors has a new attracted high interest in the wake of two important world research projects which intend to revolutionize traffic of the future by means of informatics and control engineering. In the past, the problems of state surveillance and incident detection have been solved separated by several authors. In these approaches the measurement data are processed by refined estimation method or filtering techniques to extract missing information from the time sequence of the measurements. The basic idea of the most efficient methods applied to these problems follows a common scheme, using a dynamic model for the process of traffic flow. A prediction is made for the actual measurement. The error is used by a more or less sophisticated rule to update and improve the estimates. In this way estimators have been design which under hypothesis of fixed model parameters produce good estimates for density and speed values along a section of a road. Remarkably few procedures have been proposed for the estimation of unknown or changing model parameters under the premise that traffic flow is not congested and not disturbed. Similarly, only few authors have applied this efficient estimation scheme for the purpose of automatic incident detection. No research work is reported on simultaneous estimation of system state with incident detection. Intuitively, one might expect that there is a natural boundary for the amount of information which can be extracted from a set of measurements by whatsoever sophisticated data processing method. Actually, as investigations have shown, a simultaneous estimation of traffic state with detection of incidents raises problems. Obviously, if overcharged, the above mentioned recursive estimation scheme has difficulties to interpret the prediction errors correctly when too many variations of process variables and parameters are allowed to occur. This may be understood in that way that too many ambiguous options are given for the estimator to interpret the phenomena observed indirectly in the measurement.

2. PROBLEM STATEMENT

In practice, the transitions of traffic state due to changing demand caused by weather conditions and different driver behavior may often occur at the same time. Moreover, an incident may happen at any time and should be detected by the overall surveillance system whenever it occurs. Consequently a monitoring system must cope with this situation and produce reliable estimates even under difficult conditions. In this paper, the combined estimation problem is treated. Based on theoretical analysis using selective observed data and simulation models, it is investigated that how the above mentioned separate problems can be solved simultaneously and in what combination they interfere. The limits of what can be estimated simultaneously are identified and a feasible solution to this overall surveillance problem is given. Figure 1 shows the block diagram adopted in this parer.

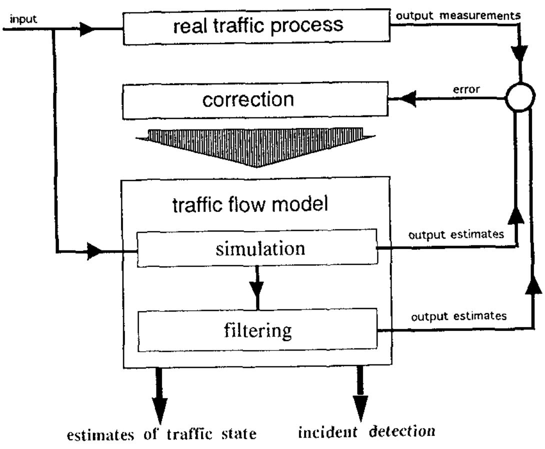

FIG.1 Block diagram of estimation scheme

We present first in the 3rd section the components of models which are necessary for estimating traffic states and detecting incidents. Then in 4th section selective observed data are introduced which are used for the theoretical analysis of the problem. The results of this analysis are underlined by simulation studies in the 5th section. At the end of the section, possible solutions to the extended estimation problems are combined with simultaneous estimation of various variables. Finally, future works are given.

3. COMPONENTS OF THE MODELS

3.1. Macroscopic Simulation Model

As it is shown in Figure 1, the most important part of estimator system is a dynamic model which comprises the rules and mechanisms by which the process variables interact and react to external influences . The model which was chosen as the most adequate for the given problem describes traffic flow dynamics by aggregate flow variables of density, average speed and volume [1][2]. Let us consider a section of a freeway which for convenience is subdivided into several road segments with a length of about 500 m (Figure 2). With respect to this space-discrete configuration the following variables of traffic flow are introduced:

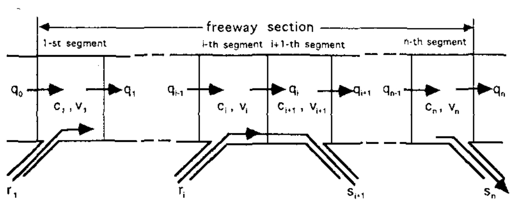

FIG. 2 Discretized section of a freeway

$c_i(k)$ traffic density in segment i [veh/km]
$v_i(k)$ *mean speed within segment i [km/hr]*
$q_i(k)$ volume from segment i into i+1 [veh/hr]
$w_i(k)$ mean speed from segment i into i+1 [km/hr]
$r_i(k), s_i(k)$ possible entering or leaving ramp volumes [veh/hr]

Using these variables, a simple balance for the vehicles within segment i at time k+1 gives the following difference equation.

$$c_j(k+1) = c_j(k) + \tfrac{T}{\Delta_j}[\alpha c_{j-1}v_{j-1} + (1-2\alpha)c_j v_j - (1-\alpha)c_{j+1}v_{j+1} + r_{j-1} - s_{j-1}]_{(k)} \quad (1)$$

The following difference equation for section *average velocity which was formulated according* to empirical observation has proved to be quite realistic

$$v_j(k+1) = v_j(k) + \tfrac{T}{\tau}[v_j(c_j) - v_j]_{(k)} + \tfrac{T}{\Delta_j}[v_j(v_{j-1} - v_j)]_{(k)} + \tfrac{\nu}{\Delta_j}\tfrac{T}{\tau}\Big[\frac{c_j - c_{j+1}}{c_j + \kappa}\Big]_{(k)} \quad (2)$$

In this equation the first bracket term on the right side reflects dynamic adaptation to the steady state speed-density characteristic $V(c_i)$, the second term accounts for the convection of foreseen density gradient in the downstream direction.
Traffic volume and mean speed which will be measured only at a distances of several kilometers (at the boundaries of the section) can be expressed within the section according to the rules of hydromechanics as a product of density and velocity. Because of the allocation at the end of segment. a weighted average seemed to be appropriate.

$$q_j(k) = \alpha c_j(k)v_j(k) + (1-\alpha)c_{j+1}(k)v_{j+1}(k) \quad (3)$$

$$w_j(K) = \alpha v_j(k) + (1-\alpha)v_{j+1}(k) \quad (4)$$

In a refined modeling approach it seems to be reasonable to make α dependent on density. With respect to the increase of computational effort when α is a function of density, it was decided to keep α constant. A dominating function within these dynamic model equation is the steady state speed-density characteristic $V(c_i)$.

$$V(c_i) = V_f\left[1 - \left(\frac{c_i}{c_{\max}}\right)^m\right]^l \quad (5)$$

where V_f is the free velocity, c_{max} denotes jam density and m and l are positive real numbers. Equations (1) to (5) for (i=1 to N) establish a nonlinear time discrete model of order 2N for the dynamic phenomena of traffic flow within the section. The equations contain a number of parameters time constant τ, density constant κ , sensitivity factor ν, weighting factor α and the four parameters in Equation (5) which have to be calibrated to bring the model close to reality. In the context of our problem, this means that on-line identification of only these two *parameters may be necessary when traffic or* weather conditions change. This was confirmed again by our investigations within the research work reported here. To complete the model description we have to formulate equations which link the measurements volume and local speed on both ends of the section to the state variables of *the model. This is not a trivial task since depending* on traffic conditions, these variables sometimes depend more on the situation inside the section sometimes more volume q_0 and local average speed w_0 at the upstream end are determined by traffic flow conditions before the section while the measurement q_n and w_n at the downstream end reflect the conditions inside the last segment. With congestion the direction of causal interaction is inverted and an opposite reasoning holds. Earlier investigations have shown that for estimator design the following assignment gave the best result. The entering volume q_0 is treated as an external input while all other measurements w_0, q_n and w_n should be treated as system reactions being connected with the state variables by:

$$q_0(k) = [c_1 v_1 - \alpha.\varepsilon(c_2 v_2 - c_1 v_1)]_{(k)} \quad (6)$$

$$w_0(k) = [v_1 - \alpha.\varepsilon(v_2 - v_1)]_{(k)} \quad (7)$$

$$q_n(k) = [c_n v_n + (1-\alpha)\varepsilon(c_n v_n - c_{n-1} v_{n-1})]_{(k)} \quad (8)$$

$$w_n(k) = [v_n + (1-\alpha)\varepsilon(v_n - v_{n-1})]_{(k)} \quad (9)$$

To overcome these difficulties, the model has to be extended to include variations of environmental road conditions and the possibility of an incident as it will be shown in the sequel.

3.2. Filtering Model:

Since the detection scheme developed in this report is based on Kalman filtering principles, an extremely brief review of concepts of the (KF) is appropriate [3]. A nominal solution of the nonlinear differential equations must exist. This solution must provide a "good" approximation to actual behavior of the system. The approximation is "good" if the difference between the nominal and actual solutions can be described by a system of linear differential equation. These equations shall be called "linear perturbation equations".

Suppose that the state x_k of a dynamical system evolves according to the vector differential equation

$$x_{k+1} = f(x_k, u_k) + w_k$$

The linearized equation can be written as:

$$x_{k+1} = A_k x_k + w_k \quad (10)$$

The independent variable (t) can be assumed the values $(t_0 \ll t_1 \ldots\ldots \ll t_N)$, where the t_i is not necessarily equidistant. The state of the system at t_k is given by the (n)-dimensional vector x_k. A_k is a known (n×n)-dimensional dynamic system matrix. where

$$A_k = \frac{\partial f}{\partial x}$$

The u_k is input variables the interval $[t_{k-1}, t_k)$. The w_k is a vector random sequence with known statistics

$$E[w_k] = 0 \quad \text{for all } (k)$$
$$E[w_k w_i^T] = Q_k \delta_{ki}$$

where δ_{ki} is the Kronecker delta. The matrix Q_k is assumed to be nonnegative-definite, so it is possible that $(w_k \equiv 0)$. Suppose that at each time t_k is available (m)-measurements y_k that is nonlinearly related to the state which is corrupted by additive noise.

$$y_k = g(x_k) + v_k$$

The linearized equation can be written as:

$$y_k = C_k x_k + v_k \quad (11)$$

C_k is a know (m×n)-dimensional observation matrix. where

$$c_k = \frac{\partial g}{\partial x}$$

The measurement will not be precise, so the errors v_k are assumed to be additive and uncorrelated between sampling times. The correlated noise processes are introduced as following.

The vector v_k is an additive random sequence with known statistics.

$$E[v_k] = 0 \quad \text{for all } (k)$$
$$E[v_k v_i^T] = R_k \delta_{ki}$$

The matrix R_k is assumed to be nonnegative-definite unless otherwise stated. Further, assumed that the random processes w_k and v_k are uncorrelated. These processes will be called white noise sequences

$$E[w_k v_i^T] = 0 \quad \text{for all } (k,j)$$
$$E[w_k x_0^T] = 0 \quad \text{for all } k$$

The mathematical model described above provides the basis for all succeeding discussion. In this paper we shall deal with a problem of considerable importance in engineering practice.

3.3. Incident Detection:

The Multiple Model (MM) method of traffic incident detection developed in present study relies strongly on Kalman Filtering theory. Therefore, in order to understand the (MM) method, some background on the Kalman Filter (KF) will be developed. Under these conditions the probability density function of r_k is given by

$$r_i(k) = (y_k - c_k \hat{x}_k)$$

$$p(r) = [(2\pi)^m |\Sigma|]^{-0.5} . e^{-\frac{1}{2}(r^T \Sigma^{-1} r)} \quad (12)$$

Σ is the precomputable covariance matrix of $r_i(.)$ and $|\Sigma|$ which represents the determinant of Σ and (m) is number vector of $r_i(k)$. The previous section has presented the equations and properties of the (KF). The principle property of interest here is test Equation (12) can be thought of as giving the instantaneous probability of observing a given residual vector $r_i(.)$. This information can be used to construct an identification method. Assume that a given linear, time-invariant "true system" is known only to be one of (N) possible systems (A_i, C_i, Q_i and R_i, i=1 to N). One (KF) is computed for each possible system and the instantaneous probability $p_i(k)$ of each residual $r_i(k)$, evaluated for (i=1 to N). These instantaneous probabilities are then combined using Equation (13), which is based on Bayes Rule, to give a posterior probability $p_i(k)$ that each hypothesized model is in fact the true system model.

$$P_i(k+1) = \frac{p_i(k)p_i(k+1)}{\sum_{j=1}^{N} p_j(k)p_j(k+1)} \qquad (13)$$

This method is summarized by Figure3.

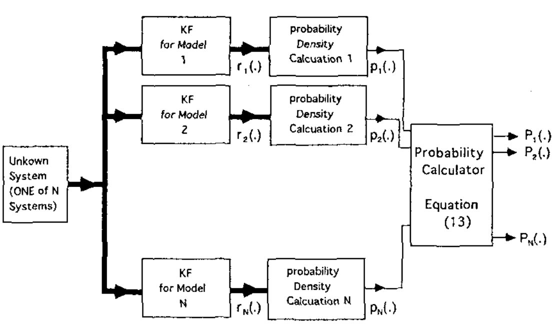

FIG.3 Flow chart of the multiple model method

4. THEORETICAL ANALYSIS

To analys simulation model, we need to use equations (1) through (9). To make initial condition, in this model q_0, r_i and s_i are measurement data. we have to divide the section into n segments. Then the amount of c_i, v_i, q_i and w_i in each segment in a given time must be estimated. These amounts after comprising to real data, show differences between real condition and estimation, By using sequential corrections on parameters to then approaching to more real results.

To analys filtering model, it is necessary to know simulation results in each step as it is expressed in equations (10) and (11). Because it is a pre-estimation for filtering. where

$$x^{\wedge}(k) = [c_1, v_1, \ldots\ldots, c_i, v_i, \ldots\ldots, c_n, v_n]^T_k$$
$$y^{\wedge}(k) = [q_1, w_1, \ldots\ldots, q_n, w_n]^T_k$$

Also by changing number and location of measurement variables, we are able to analyse various conditions. This can influences on daynamic system and observation matrix. Finally, we make sensitivity analysis of estimation. Let us assume that the first observation occurs at t_1, the sequence of operations that is performed at each sampling time can be described by the following steps;

(1) At t_k initialize p_k, $x^{\wedge}_k$ and v_k let $t = t_1$.(Reaping k = 0 to N)

(2) Form the projected estimate of the covariance of the estimate error.

$$M_k = A_{k-1,k}\ P_k A^T_{k-1,k}{}^T + v_k$$

(3) Compute the kalman gain matrix.

$$K_k = M_k C^T_{k-1,k}\ [\,C_{k,k-1} M_k C^T_{k-1,k} + w_k]^{-1}$$

(4) Form the estimation of the state at t_1 form the measurement y_1.

$$x^{\wedge}_k = A_{k-1,k} x^{\wedge}_k + Kf_k[\ y_k - y^{\wedge}_k\ ]$$

(5) Compute the covariance of the error in the estimation

$$P_k = M_k - K_k C_k M_k$$

(6) Updated time to t_2 and return to step (2) with all indices incremented by (1).

To analys incident detection, we need the results of simulation and filtering model and application of equations (12) and (13). Theoretically, one set of kalman gains is needed for each freeway condition. That is, the gain for each (KF) should be calculated separately. However, because of the nature of the differences between the various models, the kalman gains are very similar. Furthermore, recent theoretical results indicate that filter performance depend mostly on accurate dynamic modeling and on the kalman gain. Thus, the same kalman gain has been used for all KF's states to the states of the most probable model.

5. RESULTS

After this theoretical analysis the combined estimation problem was experiment by numerous simulation studies in different configurations. The measured data were partly generated by a microscopic simulation model when incident detection was included and partly by a macroscopic models as described in section (2) subjected to noise where by the initial states or parameters were treated as unknown for the estimation routine. For the estimation, the procedure of the extended kalman filter was applied to the model equations (1) through (13). Information is obtained from selected area of Metropolitan Expressways Kanagawa Route (1), Yokohane Line (K1), three sections. The first link A was chosen according to figure (2) with (8) segments, (2) on-ramp and (3) off-ramp total length of (5.13) kilometers, the second link B was chosen according to figure with (12) segments, (2) on-ramp and (1) off-ramp total length of (8.55) kilometers , third according a junction between link (A) and link B. As it is illustrated in table (1), the simultaneous estimation of different variables and points together with the Root Mean Square errors r.m.s. of measurements-simulation and measurements-filtering of flow and mean speed in the location check point with simulation and filtering conditions. Figures (4) and (5) are to be comprised between r.m.s. of simulation and filtering of estimation result about various variables and points. For example, figures (6) and (7) are shown that a short time of output in condition number (7). In figure (8) it is shown an evaluation of incident probability in a short time in the link B of segment (7) and at the same time, there is not any probability of incident in segment (2). They can be used for detection of incident.

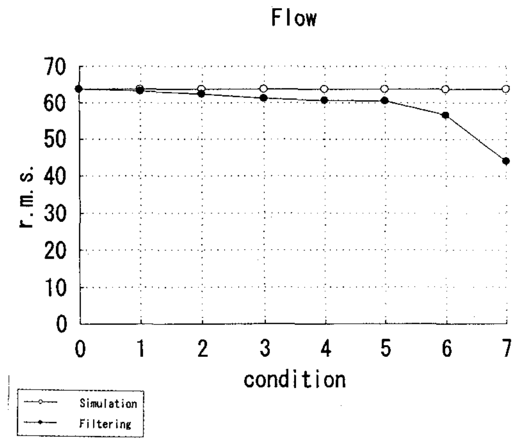

FIG.4. Effects of the number of measurement variables (Flow).

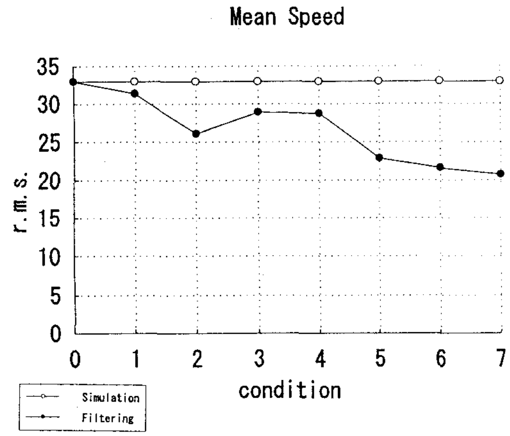

FIG.5. Effects of the number of measurement variables (Mean Speed).

Condition	Measurement (Variablies & Points)	Flow (veh/min)	Mean Speed (km/hr)	Check Point (between segment)	Model
0	q_0	63.83	32.93	2-3	Simulation
1	q_0, w_n	63.21	31.31	2-3	Filtering
2	q_0, q_n	62.51	26.07	2-3	"
3	q_0, w_0	61.21	28.92	2-3	"
4	q_0, w_0, w_n	60.71	28.78	2-3	"
5	q_0, q_n, q_n	60.58	22.85	2-3	"
6	q_0, q_n, w_n	56.61	21.60	2-3	"
7	q_0, w_0, q_n, w_n	44.05	20.71	2-3	"

TABLE.1. R.M.S. Error for each measurement condition.

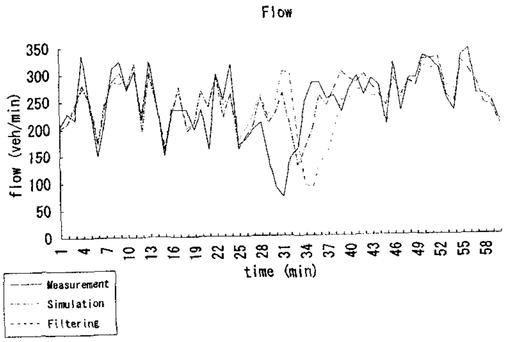

FIG.6. Comparison of estimated flows

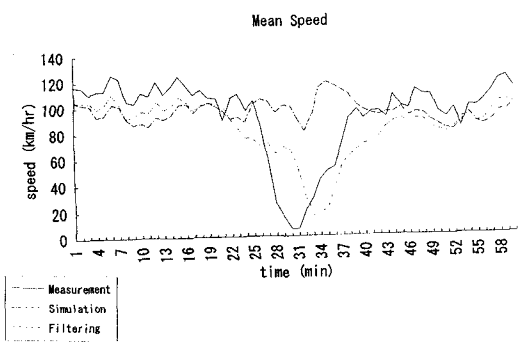

FIG.7. Comparison of estimated mean speed

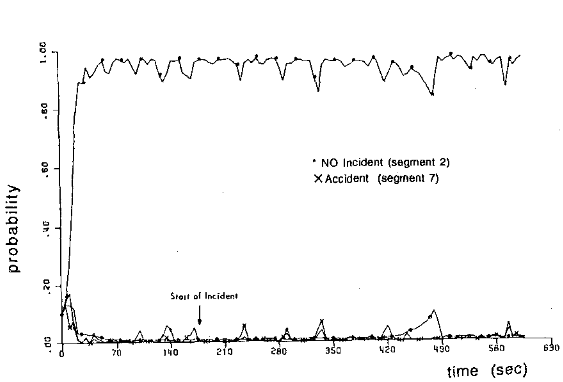

FIG.8. Evaluation of incident detection

6. CONCLUSIONS

In this paper the practical important problem of combined state estimation and incident detection for traffic flow on a section of a freeway is considered. Applied condition and model and results are classified into two groups, Simulation and Filtering estimation. In order to be capable for the substitutions for real conditions. Simulation estimation model, q_0 was regarded as a network input. Finally, we are able to approach to real condition. Filtering estimation depends on simulation estimation. Dynamic system matrix, observation matrix and error matrix are affected by measurements data. We discussed them in two sections, the first is measurement variables in which q_0, w_0, q_n and w_n are as variables. The second is measurement points in which the couple of variables in different locations are considered, such as (q_0, w_0), ... (q_i, w_i), ... (q_n, w_n). All of the couples have valuations network condition. By doing it, we are able to reduce errors and explain real conditions in better manner ($0 \leqq$ r.m.s. of filtering $\leqq$ r.m.s. of simulation).

Estimation of applied coefficient in our models, specially α and ε are affected by light traffic condition and congestion traffic condition. In other words, the value of α and ε are not stable. These coefficients also minimize the total errors.

In the future, to apply the filtering technique to extensive freeway network, we have to engage in the following;

-The improvement of traffic flow models to estimate traffic states more precisely.

-The development of sophisticated technique to detect incidents.

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