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A LITERATURE REVIEW FOR REAL-TIME ESTIMATION OF TRAFFIC STATES USING PROBE VEHICLE DATA

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1. INTRODUCTION

Reliability of traffic state variables such as speed, flow, and density requires for the development of efficient control strategies and management schemes for traffic networks in advanced traffic management systems (ATMS) and advanced traveler information systems (ATIS). On-line traffic information can be used for various purposes such as dynamic route guidance, incident detection, freeway ramp metering control, and control of variable message signs. Mathematical models to describe the traffic conditions are the key to achieve that information system since it is impossible to obtain the traffic data for a whole network by mean of field observation. In general, traffic management schemes or route guidance system applications concern with the large scale of network. Among three classes of mathematical traffic flow models, which are microscopic, mesoscopic, and macroscopic model, the macroscopic models describing the traffic states in an aggregate manner seems to be the most appropriate for real-time applications because of their lowest degree of computation and fastest simulation time. However, the results from classical static macroscopic model seem to be not sufficient for real time applications. Several strategies were introduced to integrated into the macroscopic models to use for the real-time traffic prediction. Various techniques including adaptive filtering techniques (such as artificial neural network (ANN) [13, 18], and Kalman filtering (KFT) [13]) have been used for this purpose.

Other than the typically observation techniques such as loop detectors, and video image processing techniques, traffic data can be obtained from moving vehicles, which is equipped with transmission equipment. Recently, many projects, as mentioned in [17], are working on experiment of using probe vehicles to obtain the real-time traffic data, including the ADVANCE project in Chicago, the Pathfinder project on a freeway in Los Angeles, the FAST-TRAC demonstration project in Michigan, and the project in Sydney Australia. Probe vehicles seems to be a good alternative for collecting traffic data, especially the road where the small number of detectors are installed.

The objectives of this paper are to review past researches on macroscopic traffic model development, and real-time traffic state estimation. With the intention of improving the accuracy of traffic state prediction, finally, the authors suggested an idea of using probe data to estimate the traffic states in real-time.

2. MACROSCOPIC TRAFFIC FLOW MODEL

Various forms of macroscopic traffic flow models have been proposed so far in order to improve the ability to capture the real traffic situations. They may be classified into broadly two types according to the number of partial differential equations consisting in the models.

2.1 Simple Continuum Macroscopic Model (SCM)

Lighthill and Whitham [6] proposed the macroscopic model by determining the vehicular movements in traffic flow as analogous to the particle movements in a fluid. Essential three relationships contribute to the simple continuum model. The first is the conservation of vehicles equation:

$$\frac{\partial \rho}{\partial t}+\frac{\partial q}{\partial x}=g(x,t), \tag{1}$$

where ρ is the traffic density, v is the space mean speed, q is the traffic volume, $g(x,t)$ is the generation rate (e.g., ramp-in, ramp-out), and t and x denote time and space. The second relationship is the fundamental relationship among traffic volume, speed, and density:

$$q=\rho v \tag{2}$$

The last equation is an empirical relationship between speed and density at equilibrium condition:

$$v=v_e(\rho) \tag{3}$$

One of the general expressions of equilibrium speed-density relationship is:

$$v_e(\rho)=v_f\left[1-\left(\frac{\rho}{\rho_{jam}}\right)^a\right]^b, \tag{4}$$

where ρ_{jam} is the jam density, v_f is free-flow speed and a, b are sensitivity factors which are positive numbers.

The significant feature of the SCM is the expression of the shock waves in traffic flow as characteristic speed in the model is the kinematic wave speed. However, the model contains some inherent shortcomings as pointed out by several researchers [3, 5, 7]. First, the kinematic wave theory might show the shock wave speed changes infinitely with steep speed jump. That means the SCM produces discontinuous solution even when the initial condition is smooth due to the fact that the convective term in nonlinear conservation equation is dominate. Next the model does not allow the fluctuations of speed around equilibrium because speed is determined directly from the statistical equilibrium speed-density relationship. The speed is adjusted instantanously without any delay. Furthermore, the model cannot describe the amplification of small disturbances in heavy

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traffic. It does not describe unstable traffic flow of the regular stop-start waves with amplitude-dependent oscillation. It does not describe the traffic hysteresis phenomena, i.e., the average headway of vehicles approaching a jam are smaller than those of vehicles leaving a jam.

2.2 High-order Continuum Model (HCM)

Payne [11] introduced a new relationship called the momentum equation into the SCM in stead of the equilibrium relationship. The momentum equation derived from a car-following theory and Taylor's expansion defines the variation of space mean speed over time as the following form:

$$\frac{\partial v}{\partial t}+v\frac{\partial v}{\partial x}=\frac{1}{\tau}[v-v_e(\rho)]-\frac{\nu}{\rho}\frac{\partial \rho}{\partial x}, \qquad (5)$$

where τ is the relaxation time, and ν is anticipation parameter. Three physical mechanisms can be implied from Payne' model. First, the convection term, the second term in the left side, represents the propagation of a speed difference. The relaxation term, the first term in the right side, represents the adjustment of average speed to the equilibrium speed. And the anticipation term, the second term in the right side, reflects the adjustment of the speed to foreseen traffic condition ahead.

Although Payne's model provides an improvement over the SCM, it still presents several defects. In high density conditions the model may present unrealistic high densities. One may rectify this problem by explicitly imposing constraints on speed and density so that their values do not grow unrealistically [9]. The model provides too slow relaxation, which implies unrealistic traffic behavior at abrupt changes in roadway or traffic conditions [15]. Additionally, no consideration on traffic friction caused by vehicle interactions is paid in Payne's model [9]. Later on, a variety of HCMs were developed aiming to overcome the deficiencies of Payne's model.

Papageorgiou [10] added a new term, $-\delta v g/\rho$, into Payne's momentum equation to account for the influence of on- and off-ramp traffic, where δ denotes the parameter depending upon the layout of ramp ($0 \le \delta \le 1$). g stands for on- or off-ramp volume.

Ross [15] claimed that deficiencies in Payne's model arise from equilibrium relationships between speed and density. As a result, he proposed a macroscopic model on the assumption that traffic is incompressible at jam density and without any speed-density relationship contained in it. The momentum equations are:

$$\frac{\partial v}{\partial t}+v\frac{\partial v}{\partial x}=\frac{1}{\tau}[v_f-v], \quad \rho<\rho_{jam} \qquad (6)$$

$$\frac{\partial q}{\partial x}=0, \quad \rho=\rho_{jam}, \qquad (7)$$

where v_f denotes a free flow speed, which is independent of density. In addition, capacity limit was added as another constraint. Machilopoulos [9] criticized on the physical interpretation, claiming that Ross's model does not address the anticipation and friction effects of traffic flow. As long as density is less than jam density, traffic flow is always in acceleration. In addition, it was observed that the model allows the entire queue moves at the same time with the head of a standing queue.

Semivicous model proposed by [9] and viscous model by [8] introduced a viscosity term describing traffic friction due to interactions such as lane changing at entrance and exit ramps. In addition, the models did not employ an equilibrium speed-density relationship. Consequently the momentum equation of the viscous model reduced to

$$\frac{\partial v}{\partial t}+v\frac{\partial v}{\partial x}=-\nu\rho^{\delta}\frac{\partial \rho}{\partial x}+\lambda\rho^{\zeta}\frac{\partial^2 v}{\partial x^2}, \qquad (8)$$

where λ is the viscosity parameter. δ and ζ are dimensionless constants.

Unlike the SCM, the HCMs are able to explain an amplification of small disturbances in heavy traffic, allow fluctuations of speed around the equilibrium values, and describe traffic hysteresis [7]. However, the models still have some deficiencies; First, estimations from HCM can result in negative speeds at the tail of congested regions because they have a negative characteristic speed [3, 7]. In addition, HCMs always exhibit one characteristic speed greater than the macroscopic flow velocity. This implies that future condition of traffic flow could be affected by the conditions behind (upstream), which is not realistic [3]. Recently, some models have been proposed to overcome those deficiencies. One of those is the model by Liu [7], which the momentum equation is:

$$\frac{\partial v}{\partial t}=\frac{1}{\tau(\rho)}[v_e(\rho)-v] \qquad (9)$$

Furthermore, they propose the relaxation time as a nonlinear function of density, i.e., relaxation time at a low density should be greater than that at a high density. Nevertheless, it was criticized that this model might present other inconsistencies.

The HCMs reviewed above are the macroscopic models derived from hydraulic theories. One can refer those as the high-order Payne-type models. There is another group of macroscopic models that originated from mesoscopic considerations, i.e., the gas-kinetic models. The gas-kinetic (Boltzmann-like) model, which describes the dynamics of the velocity distribution functions of vehicles in the traffic flow, was first proposed by Prigogine and Hermann [14]. Unfortunately, the gas-kinetic traffic models are not very suitable for computer simulation because they contain a large number of unknown parameters and model structures that must be estimated from traffic observations along with a large number of independent variables. It requires more complicated computation compared to macroscopic models. Hence many researchers, such as Phillips [12], and Helbing [4], have applied the concept of gas-kinetic models to develop the macroscopic traffic flow models. For instance, the model of Phillips expresses the momentum equation as:

$$\frac{\partial v}{\partial t}+v\frac{\partial v}{\partial x}=\lambda(\rho)[v-v_e(\rho)]-\frac{1}{\rho}\frac{\partial P}{\partial \rho}\frac{\partial \rho}{\partial x}, \quad (10)$$

where $P(\rho,v)$ is traffic pressure defined as the product of density and the variance of traffic speed distribution. This kind of models has a potential for development of multi-lane or multi-class model. However, their calculations are still very lengthy and rather difficult, and complicated to estimate the parameters.

3. TRAFFIC STATE ESTIMATION

Classical methods to estimate traffic states are to use mathematical models to describe the traffic variables. Thus, the improvement of traffic flow models plays a significant role for traffic state estimation. Other than the choice of model form, the accuracy of traffic estimation depends on the model calibration through an adjustment of the model parameters according to the traffic pattern and roadway geometry of a particular site. Moreover, numerical scheme to solve the differential equations (discretization) also has a significant effect on the accuracy and efficiency of model, as illustrated in Lui [7], Michalopoulos [9], Lyrintzis [8]. Accordingly, before using any model, one should realize that the outcomes of continuum model are very sensitive to the data and to the numerical approximation used [3]. The models should be carefully calibrated for a certain traffic condition.

To enhance the traffic state estimation, several strategies have been introduced into this problem, such as the use of neural network, KFT, etc. The examples of this application are: Zhang [18] developed a feed-forward ANN to emulate a high-order continuum traffic flow model; Pourmoallem [13] integrated a ANN into the macroscopic model combined with the KFT.

4. KALMAN FILTER TECHNIQUE (KFT)

KFT was introduced to traffic flow engineering as a tool to improve traffic control and management applications. Other than the estimation of traffic states, it was used for estimation of travel time in Chen [1], and parameter identification in Cremer [2], etc. KFT has a potential for online traffic control systems because it can estimate traffic states in real time based on a feedback concept without any driver's behavior model. Moreover, it is suitable for real-time digital implementation because of its recursive algorithm. By applying the KFT to a macroscopic traffic model, traffic states are estimated by the macroscopic model and then adjusted according to KFT algorithm. The adjustment of state variables at a certain time increment is proportional to the difference between real observation and model prediction values of observation variables at the previous time step.

To apply KFT with a macroscopic traffic flow model for estimation of traffic states, traffic density and space mean speed are considered to be the state variables, where as traffic volumes and spot speeds are treated as obsevation variables. Thus the state variable vector, $x(t)$, and the observation variable vector, $y(t)$ are:

$$x(t)=(\rho_1, v_1, \ldots \rho_i, v_i, \ldots \rho_n, v_n)^T_{(t)}, \quad (11)$$

$$y(t)=(q_0, w_0, \ldots, q_m, w_m)^T_{(t)} \quad (12)$$

where w is the time mean speed. n denotes the number of segment, and m denotes the number of observation points. To formulate KFT, Eq. 1 and a momentum equation were treated as state equation, while the observation equation consists of Eq. 2 and the presumed relationship between spot speed and state variables. In addition, the white noise errors were induced in both macroscopic model formula and measurement process. Thus, the state equation becomes as follow:

$$x(t+1)=f[x(t)]+Bu(t)+\xi(k) \quad (13)$$

The observation equation is,

$$y(t)=g[x(t)]+\zeta(k). \quad (14)$$

where $u(t)$ is the inflow volume from inflow links; B is the coefficient matrix; $\xi(t)$ and $\zeta(t)$ are noises vectors representing the modeling errors and measurement errors, respectively. Finally, the state and observation equations are linearized around the nominal solution, $\tilde{x}(t)$ using Taylor's expansion. The model becomes:

$$\tilde{x}(t+1)\cong A(t)x(t)+b(t)+Bu(t)+\xi(t) \quad (15)$$

$$\tilde{y}(t)\cong C(t)x(t)+d(t)+\zeta(t) \quad (16)$$

where $A(t)=\frac{\partial f}{\partial x}$, $b(t)=f[\hat{x}(t)]-\frac{\partial f}{\partial x}\hat{x}(t)$

$C(t)=\frac{\partial g}{\partial x}$, $d(t)=g[\tilde{x}(t)]-\frac{\partial g}{\partial x}\tilde{x}(t)$

$\tilde{x}(t)$ is the estimated state vector before observing new data, $y(t)$. $\hat{x}(t)$ is the updated vector after obtaining actaul observation variables, $y(t)$. The state variables can be adjusted according to the correction steps of KFT as:

(1) $\tilde{x}(t)=f[\hat{x}(t-1)]$

(2) $M(t)=A(t-1)P(t-1)A^T(t-1)+\Xi$

(3) $K(t)=M(t)C^T(t)[C(t)M(t)C^T(t)+Z]^{-1}$

(4) $\tilde{y}(t)=g[\tilde{x}(t)]$

(5) $\hat{x}(t)=\tilde{x}(t)+K(t)[y(t)-\tilde{y}(t)]$

(6) $P(t)=M(t)-K(t)C(t)M(t)$

(7) set $t=t+1$, and then repeat the whole steps untill the required simulation time step is reached. Ξ and Z are covariance matrices of $\xi(t)$ and $\zeta(t)$, respectively.

5. ACQUIREMENT OF TRAFFIC DATA

Traffic density and average speed are the preferable measure of traffic flow for several reasons; they are the variables that can be directly used in ramp control algorithm. Formerly, section densities and speeds can be obtained only through aerial photography, which is quite cumbersome. Moreover, such a technique cannot be employed in real time applications. Nowadays, the most common mechanism for traffic data collection is the traffic detector. Traffic detector data provide the information of traffic volume directly, while traffic density and average speed has to be interpreted from percent occupancy and spot speed, respectively. The shortcomings of traffic detector are that the error in counting may occur occasionally, such as in case of the vehicle has more than two axles. As the network is larger the number of detectors required for efficient network surveillance is increasing.

A new traffic data collection technique, namely probe vehicle technique, attracts much attention recently. Vehicles are used as the probes to experience the traffic conditions which they traverse and transmit the traffic information to a traffic information center [17]. The procedure is performed as real-time manner. Additionally, the data from the links that no detector installed can be obtained. The probe vehicles can collect several types of information. As in ADVANCE project, the major information collected by probe vehicles are link ID with lane used, link travel time, congested time, and congested distance [16].

Several researchers studied about the application of probe vehicles. Sen [16] used probe data to estimate travel time for arterial road and determine the number of suitable probe vehicles. They found that after a certain number of probes , additional probes do not significantly decrease the variance of estimate. Therefore, the high level of probe deployment is not reasonably good quality, as long as all important links are covered by at least a few probes. Srinivasan [17] found that the number of probes required depends on the measurement time interval (less measurement period, require more probes), size of network, and traffic condition. Chen [1] used KFT to perform travel time prediction based on real time information provided by probe vehicles.

6. CONCLUSION AND SUGGESTION FOR FUTURE WORK

Traffic state estimation plays an important role in traffic control and management strategies. Mathematical models were continuously developed aiming to improve the ability to describe real traffic situations. To suit with the real-time applications, some additional algorithms, such as KFT, and ANN, were integrated into the macroscopic model.

Probe vehicle seems to be a valuable source of real-time traffic information. Currently many projects concern with assessing the feasibility of using probe vehicles to collect real time traffic data for advanced traffic management and information systems. However, so far, the probe data are used mainly to estimate travel time. There is no attempt to use that kind of information to improve the estimation of traffic state (i.e., speed, flow and density). Consequently, future work of the authors will be focus on using probe data to improve the traffic state estimation. The travel times from probe data may be converted to the speeds to use as additional observation variables for the KFT with some adjustments in the formulation.

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