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A Framework of Real-Time Traffic Information System

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Abstract: - In this paper, a framework of real-time macroscopic traffic simulation is proposed. Real-time traffic simulation using macroscopic traffic flow model on freeway have been studied and implemented in the past. We introduced a framework of implementing real-time traffic simulation on urban network. To implement the simulation on an urban network, the estimation of origin-destination (O-D) matrix must be considered. Thus the framework consists of 1) Path generation, 2) Dynamic Origin-Destination Estimation and 3) Link Dynamics. Path generation is based on the Wardrop's user equilibrium concept and modified convex combination algorithm. State space model is used in dynamic O-D estimation, while the LWR model is used to describe the macroscopic traffic flow in Link Dynamics. This study implements the simulation with real-time traffic input and predict traffic condition in real-time. An empirical example is conducted on a real network consists of 91 nodes and 244 links.

Key-Words: - ITS, Traffic simulation, Dynamic O-D, Macroscopic traffic flow model

1 Introduction

Traffic simulation techniques appeared in the early 1950s in the field of transportation science. Computer-based traffic simulation tools, mostly developed in the past one or two decades, exist as a cost-effective assisting tool for researchers and practitioners to verify and evaluate traffic management strategies. An important goal of the traffic simulation tools is to be used as a computational component in a real-time traffic system. The system would be inputted with real-time traffic data, and predict traffic conditions in real time [1]. Simulation models can be characterized as microscopic, mesoscopic or macroscopic, numbers of simulation packages existing today are 65, 3 and 16 respectively.

The microscopic models simulate every vehicle in the network; mainly include three behaviors, accelerations, decelerations and lane changes. This kind of models, try to describe the actions and reactions of the vehicle that make up the traffic as accurately as possible, are the so-called car-following model. In order to achieve accuracy in modeling the traffic, it leads to a simulation model with high degree of parameters (50 parameters is common). The simulation time heavily depends on the number of vehicle that exist simultaneously in the simulated network, that make it hard to meet the requirements of simulating large-scale traffic networks for ITS applications, especially at real-time level [2].

The mesoscopic models tend to model the individual vehicles, but describe their behavior in a simplified manner. Some types of these models group individual vehicles into cells which control their behavior. The cells traverse the network and vehicles can enter and leave cells when needed [3]. Some types of these models group vehicles into packets travel along the network and act as one entity. Vehicle packets are continuous in time, but interact only through an underlying time-sliced macroscopic traffic model [4]. Another type of mesoscopic models uses cellular automata where the road is discretized into cells that can either be empty or occupied by a vehicle [5].

The macroscopic approach, based on an analogy between traffic flow and a real fluid flow, is also called continuum traffic-flow model [6]. These models mainly based on traffic density, volume and speed have been widely analyzed in the past [7][8][9][10]. Macroscopic models usually involve partial differential equations defined on appropriate domains with boundary conditions describing traffic phenomena. The models present a higher level of abstraction than the microscopic model and lead to some computing advantages. The computing time required for a macroscopic model do not increase with the number of existing vehicle on the simulation network, and this advantage makes it easier to implement on a large-scale network.

The major objective of this paper is to illustrate a real-time traffic simulation system with real-time traffic input, by macroscopic traffic model on a real urban network. Some results on the topic of real-time traffic simulation were presented by Chronopoulos and Johnston [1]. They've shown that the real-time traffic simulation process is feasible on a freeway. The main difference between this paper and that of Chronopoulos and Johnston is: This model implements the real-time traffic simulation process on an urban network. That means the assignment of real-time origin-destination (O-D) matrix and path flow must be considered, which in many other simulations are either done off-line or be assigned as an input [11].

The content of the article will be followed by 1) the framework and the elements of the real-time traffic simulation is discussed, 2) the system implementation, and 3) the conclusions.

2 The Framework of Real-Time Traffic Simulation

In this section, overall framework of the real-time simulation is described. Then the main elements, path generation, dynamic origin-destination estimation, and link dynamics, are presented. The simulation begins with loading network structure, and then the path generation will generate possible path set for dynamic origin-destination estimation. By using the possible path set and real-time traffic data from the surveillance system, dynamic origin-destination estimation will estimate the path flow. With the network structure information, path flow can be transformed into link flow, and then send to the procedure of link dynamics. In the procedure of link dynamics, the link flow and the signal timing phase information is been transformed into boundaries condition of macroscopic traffic model. After solving the traffic model, travel time information is then generated as the system output. The framework of this simulation is shown as figure 1.

2.1 Path Generation

In this simulation, a path generation is introduced to generate possible path set for the given origin and destination vertex of the simulation network. This study generates possible path by solving Wardrop's user equilibrium principle.

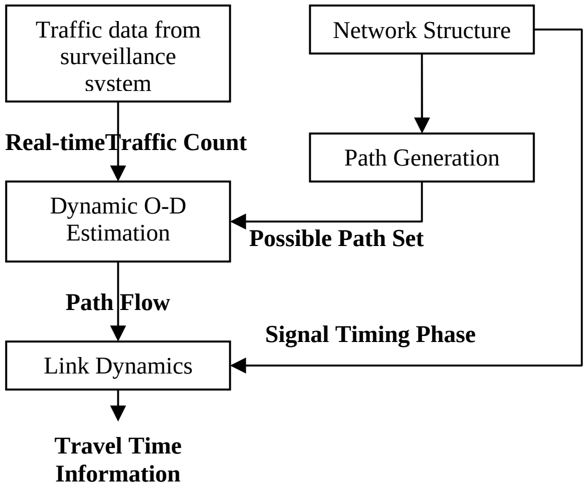

Fig. 1 The framework of real-time simulation.

The most classical formulation for solving user equilibrium is Beckmann's transformation [18]. The convex objective function and a linear constraint set of user equilibrium is

$$\begin{aligned} \min \quad & z(x) = \sum_a \int_0^{x_a} t_a(\omega)d\omega \\ s.t. \quad & \\ & \sum_k f_k^{rs} = q_{rs} \quad \forall r,s \\ & f_k^{rs} \geq 0 \quad \forall k,r,s \end{aligned} \tag{1}$$

where x_a is the flow on link a, f_k^{rs} is the flow on path k connecting origin r with destination s, and the incidence relationship $x_a = \sum_{rs} \sum_k f_k^{rs} \delta_{a,k}^{rs}, \ \forall k$, hold. $\delta_{a,k}^{rs}$ is an indicator variable, it equal to 1 if link a is on path k between O-D pair r-s, equal to 0 otherwise.

A convex combination algorithm is applied to the user equilibrium objective function to solve the problem [19]. In this simulation the algorithm is modified to generate the path set. When applied to the solution of the user equilibrium problem, the solution algorithm A can be summarized as follows,

- *Step A-1 Initialization*
  Set counter n:=1. Path set $p = \{\phi\}$.
  Perform all-or-nothing assignment based on t_a=t_a(0), $\forall a$. Store path information generated in the path set p. This yields $\{x_a^1\}$.

- *Step A-2 Update.*
  Set $t_a^n = t_a\left(x_a^n\right), \quad \forall a$.

- *Step A-3 Direction finding.*
  Perform all-or-nothing assignment based on $\left\{t_a^n\right\}$. If the path generated in all-or-nothing assignment exists in *p*, go to step 7. Otherwise, this yields a set of flows $\left\{y_a^n\right\}$.

- *Step A-4 Line search.*
  Find α_n that solves
  $$\min_{0\le\alpha\le1}\sum_a\int_0^{x_a^n+\alpha\left(y_a^n-x_a^n\right)}t_a\left(\omega\right)d\omega$$

- *Step A-5 Move.*
  Set $x_a^{n+1}=x_a^n+\alpha_n\left(y_a^n-x_a^n\right),\quad\forall a$.

- *Step A-6 Convergence test.*
  If $Max\left\{\left|x_a^{n+1}-x_a^n\right|\right\}\le\varepsilon$, go to step 7. Otherwise, set *n*:=*n* + 1 and go to step 2.

- *Step A-7 Stop.*
  Path set *p* would be the equilibrium path set and $\left\{x_a^n\right\}$ would be the equilibrium link flow.

2.2 Dynamic Origin-Destination Estimation

Origin-Destination (O-D) data is very useful in many transportation related domains; real-time O-D data is especially important in the Advanced Traffic Management System (ATMS) and Advanced Traveler Information System (ATIS) [12][13][14]. Traditional O-D data collection techniques are very costly and not possible to obtain in real-time, thus researchers have been seeking less expensive estimation methods to derive real-time O-D data. Jou introduce the state space model into dynamic O-D estimation, which estimate O-D matrices and transition matrix simultaneously without any prior information of state variables, while other studies assume that the transition matrix is known or at least approximately known [15]. The standard state space model is coupled with two parts: transition equations and observation equations. First, the state equation which assumed that the O-D flows at time *t* can be related to the O-D flows at time *t*-1 by the following autoregressive form,

$$x_t=Fx_{t-1}+u_t,\ t=1,2,3,...,n \qquad (2)$$

where x_t is the state vector which is unobservable, *F* is a random transition matrix and $u_t\sim N_p\left(0,\Sigma\right)$ is independently and identically distributed noise term. N_p denotes the *p* - dimensional normal distribution, Σ is the corresponding covariance matrix. *x*, the state variable vector, defined to be the path flow belonging to O-D pairs. The observation equation,

$$y_t=Hx_t+v_t,\ t=1,2,3,...n \qquad (3)$$

where y_t is the $q\times1$ observation vector which means there are *q* detectors on the road network. The number of O-D pairs is denoted by *p*. *H* is a $q\times p$ zero-one matrix, which denotes routing matrix for a network. v_t is also a noise term that $v_t\sim N_q\left(0,\Gamma\right)$. Both *x* and *F* are unobservable, thus Kalman filter is not suitable to directly estimate and forecast the state vector. Hence, Gibbs sampler is used to tackle the problem of simultaneous estimation of *F* and x_t by latest available information. The solution algorithm *B* is shown as follows,

- *Step B-1 (Initialization)*
  1. Use prior information to generate $F^{(0)}$.
  2. Given Σ and Γ.
  3. Given $x_0\sim N(\mu_0,V_0)$.

- *Step B-2 (Generate $x_t^{(g)},\ t=0,1,2,...,n$)*
  1. Generate $x_0^{(g)}$ from $N\left(\mu_0,V_0\right)$.
  2. Generate $x_1^{(g)}$ from
     $x_1\left|x_0^{(g)},\ F^{(g)}\sim N\left(F^{(g)}x_0^{(g)},\Sigma\right)\right.$
  3. Use the Kalman Filter to filter $x_1^{(g)}$.
  4. Repeat 2, 3 for t = 2, 3, 4, … , n.

- *Step B-3 (Generate $F'^{(g)}$)*
  1. Calculate $A^{(g)}=\left\{a_{ij}^{(g)}\right\}$,
     $a_{ij}^{(g)}=\left(X_{n(i)}'^{(g)}-X_{n-1}'^{(g)}\hat{F}_i'^{(g)}\right)'\left(X_{n(j)}'^{(g)}-X_{n-1}'^{(g)}F_j'^{(g)}\right)$
     and $\hat{F}_i'^{(g)}=\left(X_{n-1}^{(g)}X_{n-1}'^{(g)}\right)^{-1}X_{n-1}^{(g)}X_{n(i)}'^{(g)}$.
  2. Calculate $X_{n-1}^{(g)}X_{n-1}'^{(g)}$.
  3. Generate $w\sim Wishart\left(X_{n-1}^{(g)}X_{n-1}'^{(g)},n-p\right)$.
  4. Generate $Z=\left(z_1',z_2',z_3',...,z_p'\right)$,
     $z_k\overset{iid}{\sim}N_p\left(0,A^{(g)}\right)$.
  5. Generate $F'^{(g)}=\left(\left(w^{\frac{1}{2}}\right)'\right)^{-1}Z$.

- *Step B-4 (Iteration)*
  Repeat *Step 1-2* and *Step 1-3* for *m* times, then we'll have $\left\{X^{(1)},...,X^{(m)}\right\}$.

- *Step B-5 (Estimate X and F')*

Repeat *Step 1-1* to *Step 1-4* for k times, then we'll have $\left\{X_{(1)}^{(m)},...,X_{(k)}^{(m)}\right\}$. Finally, estimate X and F' by $\hat{X}=\frac{1}{k}\sum_{n=1}^{n=k}X_{(n)}^{(m)}$ and $\hat{F}'=\frac{1}{k}\sum_{n=1}^{n=k}\hat{F}'^{(m)}_{(n)}$.

2.3 Link Dynamics

The model of link dynamics in the simulation is described in this section. It'll follow by the macroscopic traffic models and the consideration of signal effect to the link.

2.3.1 Macroscopic traffic continuum models

Macroscopic traffic continuum models had been classified into first-order continuum models, such as Lighthill, Whitham and Richards' well-known flow conservation model (LWR model), and high-order continuum models, such as Payne's momentum conservation models (PW model) [16]. The models are composed of one or several partial differential equations (PDEs) defined on appropriate domains with initial and boundary conditions.

The model been used in the simulation is the LWR model, the classical scalar conservation law developed by Lighthill and Whitham and Richard. The LWR model consists of the fundamental conservation principle in the form of a PDE,

$$\frac{\partial k(x,t)}{\partial t}+\frac{\partial q(k)}{\partial x}=g(x,t) \tag{4}$$

together with standard definition of flux function

$$q(k)=k(x,t)\times u(k) \tag{5}$$

It is assumed that the empirical u-k relationships follow the Greenshields traffic stream model

$$u(k)=u_f\times(1-k/k_b) \tag{6}$$

where u_f denote the free flow speed and k_b the density with vehicles bumper to bumper. Since it is difficult to find the analytical solution of the traffic continuum model, numerical methods, such as Lax or Upwind method, had been used by researchers to simulate the numerical solutions for traffic continuum models [8]. Lax-F finite difference method is used in solution scheme. For convenience, we use the following notations:

Δx : uniform step size of space grids

Δt : uniform width of time mesh

Δt_n : adaptive width of time mesh at time $t_0+\sum_{i=1}^{n}\Delta t_i$

k_j^n :density at time $t_0+n\Delta t$ (or $\sum_{i=1}^{n}\Delta t_i$) and space $j\Delta x$

q_j^n : flow at time $t_0+n\Delta t$ (or $\sum_{i=1}^{n}\Delta t_i$) and space $j\Delta x$

u_j^n : speed at time $t_0+n\Delta t$ (or $\sum_{i=1}^{n}\Delta t_i$) and space $j\Delta x$

g_j^n : net entering or leaving rate of vehicle at time $t_0+n\Delta t$ (or $\sum_{i=1}^{n}\Delta t_i$) and space $j\Delta x$

Lax-F scheme transfer PDEs to finite difference equations by using centered difference skill. The Lax-F difference equation of LWR continuum model can be written as

$$k_j^{n+1}=\frac{k_{j+1}^n+k_{j-1}^n}{2}-\frac{\Delta t}{\Delta x}\frac{q_{j+1}^n+q_{j-1}^n}{2}+\frac{\Delta t}{2}\left(g_{j+1}^n+g_{j-1}^n\right) \tag{7}$$

where $q_j^n=k_j^n\times u_j^n$ and $u_j^n=u_f\times(1-k_j^n/k_b)$.

General finite difference methods usually require the uniform space mesh and the uniform time mesh. In order to satisfy the Courant-Friedrichs-Lewy (CFL) condition, explicit finite difference methods would generate many tiny time step sizes in simulating traffic continuum model. In order to improve the computation performance, Cho designed a finite difference scheme with adjustable time mesh to solve the hyperbolic traffic flow model. The next time size can be determined by calculating the ratio of uniform space mesh size and maximal slop of characteristic curve at current stage, can be expressed as

$$\Delta t_{n+1}=\frac{\Delta x}{\sup_{k\in R}\left|q^n(k)_k\right|} \tag{8}$$

The solution algorithm C of the adaptive Lax finite difference scheme for the LWR model is as the following four steps.

- *Step C-1 (Initialization)*
  1. Given function form of $g(x,t)$ and $u(k)$, and all the corresponding parameters, such as u_f and k_b.

2. Given total road length, *X*, and number of gridlines in space, *m*, then $\Delta x = X / m$. And total time interval *T*.
3. Given initial condition, $k(x,0)$, and boundary condition, $k(0,t)$, of the LWR model.

- *Step C-2*
  Selecting maximal slop of characteristic curve from the m+1 grid points at time level n

$$\rho_{n+1} = \sup_{k \in R} \left| q^n(k)_k \right|$$

- *Step C-3*
  Determining the adaptive time mesh and updating density values for next time period:

1. If $\rho_{n+1} \geq k$, then
   (a) $\Delta t_{n+1} = \dfrac{\Delta x}{\rho_{n+1}}$
   (b) $t_{n+1} = t_n + \Delta t_{n+1}$
   (c) Compute the density values via (7)
2. If $\rho_{n+1} < k$, then
   (a) Let $c = 0$
   (b) $\Delta t_{n+1} = (T - t_n) / 2^c$
   (c) $t_{n+1} = t_n + \Delta t_{n+1}$
   (d) Compute the density values via (7)
   (e) If $k(x,t_{n+1})$ not converge, then $c = c + 1$ and repeat (b), (c), (d) and (e).

- *Step C-4 (Iteration)*
  1. Let $n = n + 1$
  2. Repeat *Step C-2, C-3,* and *C-4* until $t_{n+1} \geq T$ then stop.

2.3.2 Signal Phase
As mentioned in 2.3.1, the macroscopic models are composed of PDEs defined on appropriate domains with initial and boundary conditions. After the dynamic O-D estimation, the flow of each link would be obtained. The flow will be transferred, by the flow-density relation function, into the upstream boundary of the model. The free boundary condition is suitable for absorbing boundaries, should be used if the traffic situation outside the boundaries is not of interest [17]. The absorbing boundary in not suitable for the urban traffic simulation, because the signal control device changes periodically and lead to the change of downstream boundary.

3 The System Implementation
The implementation of the real-time simulation framework is discussed in this section. This section consists of the implementation platform (software and hardware environment) and an empirical example of real network.

3.1 Software and hardware environment
The simulation is implemented in C++ programming language, which can be re-compiled on different platforms. Executing on PCs with Windows and Linux operating system has been confirmed. The implementation of the simulation dos not limited to the size of networks, the only limitation is memory available on the computer. Not like the microscopic simulation, the computing speed of this simulation is based on the size of network not the number of vehicle that exists in the simulated network. With this characteristic, the simulation of the same network will be nearly constant whether the traffic is jammed or not.

3.2 Example
The real-time simulation is implemented on a real network located in Taiwan, the HsinChu Science-based Industrial Park. The network is a closed network, with 11 entrances, which consists of 91 nodes and 244 links, shown as figure 2.

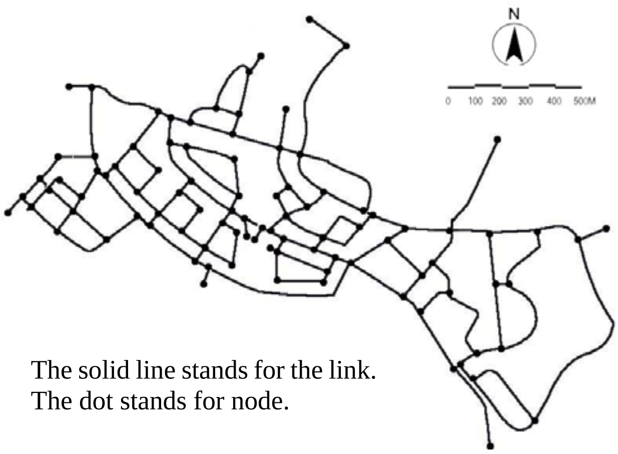

Fig. 2 The simulation network.

The experiment of simulation were conducted on a XEON 2.4GHz Linux-based PC with 2Gb of memory. GNU C++ compiler is used for the compilation. With the space mesh size Δx = 20m and adaptive time mesh, the simulation of 15 minutes operation on the network requires approximately 7 minutes of executing time. This enable the simulation to predict the traffic condition in real-time.

4 Conclusion
This paper proposed a framework of real-time traffic simulation on an urban network by dynamic O-D

estimation and macroscopic traffic model. This simulation framework is implemented on C++ programming language and has the ability to be ported to various platforms. An experiment is conducted on real road network by a Linux-based PC. The empirical test shows the ability of real-time simulation of a real network.

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References:

[1] Anthony Theodore Chronopoulos and Charles Michael Johnston, A Real-Time Traffic Simulation System, *IEEE Transactions on Vehicular Technology*, Vol. 47, No. 1, 1998, pp. 321-331.

[2] Qi Yang and Haris N. Koutsopoulos, A Microscopic Traffic Simulator for Evaluation of Dynamic Traffic Management Systems, *Transportation Research: Part C*, Vol. 4, No. 3, 1996, pp. 113-129.

[3] Moshe E. Ben-Akiva, Haris N. Koutsopoulos, R. Mishalani ,and Qi Yang, Simulation Laboratory for Evaluating Dynamic Traffic Management Systems, *ASCE Journal of Transportation Engineering*, Vol. 123, No. 4, 1997.

[4] Nicholas B. Taylor, The CONTRAM dynamic traffic assignment model, *Networks and Spatial Economics*, Vol 3, 2003, pp. 297-322.

[5] Nino Boccara and Hnryk Fuks, Critical behaviour of a cellular automaton highway traffic model, *Journal of Physics A: Mathematical and General*, Vol. 33, 2000, pp. 3407-3415.

[6] Laurent Magne, S. Rabut ,and J.-F. Gabard, Towards an hybrid macro-micro traffic flow simulation model, *INFORMS Salt Lake City String Conference*, 2000

[7] M. H. Lighthill and G. B. Witham, On kinematic waves II: a theory of traffic flow on long crowded roads, *Proceeding of the Royal Society*, Vol. A229, 1955, pp.317-345.

[8] H. J. Payne, FREEFLO: A macroscopic simulation model of freeway traffic, *Transportation Research Record*, Vol. 772, 1979, pp. 68-75.

[9] C. J. Leo and R. L. Pretty, Numerical Simulation of macroscopic continuum traffic models, *Transportation Research*, Vol. 26B, No. 3, 1990, pp.207-220.

[10] D. Helbing, Improved Fluid-Dynamic Model for Vehicular Traffic, *Physical Review E*, Vol. 51, No. 4, 1995, pp. 3164-3169.

[11] Staffan Algers, E. bernauer, M. Boero, L. Breheret, C. D. Taranto, M. Dougherty, K. Fox ,and J. - F. Gabard, *A Review of Micro-Simulation Models*, SMARTEST Project Deliverable No. 3, 1998.

[12] David Bernstein, T. L. Friesz, Z. Suo ,and R. L. Tobin, Dynamic Network User Equilibrium with State-Dependent Time Lags, *Networks and Spatial Economics*, Vol. 1, 2001, pp. 319-347.

[13] Gang-Len Chang and X. D. Tao, An integrated model for estimating time-varying network origin-destination distributions, *Transportation Research*, Vol. 33A, 1999, pp. 381-399.

[14] Pei-Wei Lin, G.-L. Chang ,and S. Rahwanji, Robust Model for Estimating Freeway Dynamic Origin-Destination Matrix, *Transportation Research Board*, 2005.

[15] Yow-Jen Jou, M. C. Hwang, Y. H. Wang ,and C. H. Chang, Estimation of Dynamic Origin-Destination by Gaussian State Space Model with Unknown Transition Matrix, *Proceeding of 2003 IEEE International Conference on System, Man and Cybernetics*, Vol. 1, 2003, pp. 96-101.

[16] Hsun-Jung Cho, M.-C. Hwang, ,and T.-J. Jou, A finite difference method with adaptive time mesh for hyperbolic traffic flow, *Proceeding of 2002 IEEE International Conference on ITS*, Vol. 1, 2002, pp.779-784.

[17] D. Helbing and M. Treiber, Numerical simulation of macroscopic traffic equations, *IEEE computational Science and Engineering*, Vol. 1, 1999, pp. 89-98.

[18] M. J. Beckmann, C. B. Mcguire ,and C. C. Winston, *Studies in the economic of transportation*, Yal University Press, 1956.

[19] Yosef Sheffi, *Urban Transportation Networks: Equilibrium Analysis with Mathematical Programming Methods*, PrenticeHall, 1985.