AN INNOVATIVE PROPOSAL FOR REAL-TIME OD FLOW ESTIMATION ALGORITHM FOR LARGE TRAFFIC NETWORKS

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1. Introduction

Direct measurement of real-time OD flows for large traffic networks is costly and time consuming process. Researchers therefore have been concentrating on OD flow estimation methods with less expensive data mainly obtained from detectors. This paper also attempts to propose an innovative algorithm for real-time OD estimation from detector data focusing on three significant issues.

The first issue can be noticed in a conventional OD flow estimation approach for a large traffic network with *n* origins and *m* destinations. The available data for OD estimation are set of origin flows (O_r^t, $r = 1,\ldots n$) and destination flows (D_s^t, $s = 1,\ldots m$). Initiating from the relationship of OD flows with origin flows and destination flows respectively given by equations 1 and 2, we can obtain possible set of OD flows. The superscript *t* denotes the time interval.

$$\sum_{i=1}^{m} q_{ri}^t = O_r^t \quad \ldots\ldots\ldots (1) \qquad\qquad \sum_{j=1}^{n} q_{js}^t = D_s^t \quad \ldots\ldots\ldots (2)$$

The problem become thus challenging, because the number of available equations (*n* or *m*) are smaller than the unknown OD flows (*n* x *m*) to be estimated in OD matrix.

The second issue arises in another conventional approach utilizes link traffic flows for OD flow estimation. It follows that the problem of formulating a relationship between available link traffic flows and OD flows treated in various ways. To overcome the complexity in formulating such a relationship, assignment proportions were proposed to map between the link traffic flows and OD flows (Ashok et al., 2000; Ashok et al., 2002). This formulation can be represented by

$$x_l^T = \sum_{T-t}^{T} a_{rs,t}^T q_{rs}^t + w_l^T \qquad \ldots\ldots\ldots \quad (3)$$

where
- x_l^T represents the observed traffic flows at link *l* during time interval *T*
- $a_{rs,t}^T$ represents the assignment proportions of OD flow between OD pair *rs* departed its origin during time interval *t* and observed at link *l* during time interval *T*
- q_{rs}^t represents the OD flow between OD pair *rs* departed its origin during time interval *t*
- w_l^T represents the measurement error of traffic flows at link *l* during time interval *T*

To derive time-dependant assignment proportions, time-dependent travel times obtained from traffic surveillance system or from a dynamic simulation model were used. In reality travel times are indirectly depends on OD flows. But neglecting the effect of travel time, most of these approaches treated assignment matrix simply as a coefficient to map between the link traffic flows and OD flows. Thus the real-time OD flow computation becomes erroneous. In fact the relationship between link traffic flows and OD flows is nonlinear cannot simply be expressed in a closed analytical form.

Pueboobpaphan (2007) have noted this problem and proposed an OD parameter estimation algorithm by eliminating the need of computing assignment matrix. The nonlinear relationship between link traffic flows and OD flows was captured through macroscopic traffic simulation model. Further the algorithm incorporated unscented kalman filter (UKF) for feedback estimation utilizing actually measured link traffic flows.

[*] Key Words: Real-time OD flows, traffic distribution model, traffic assignment model, macroscopic model
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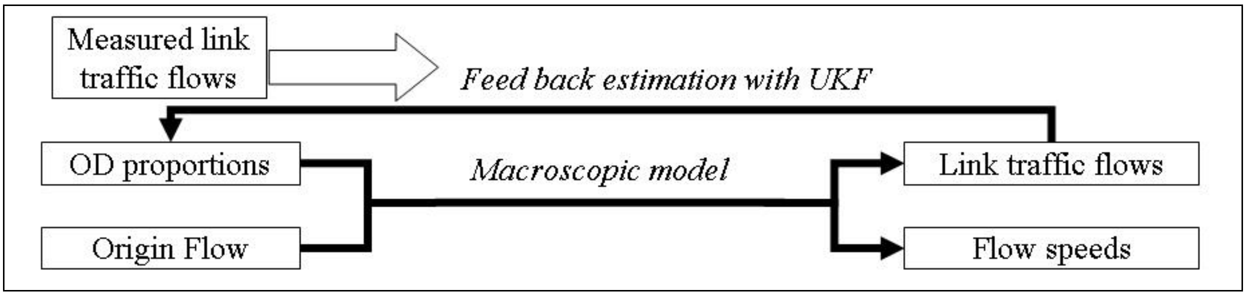

Figure 1 : Pueboobpaphan 's OD flow estimation algorithm

The fundamental concept of Pueboobpaphan, depicted in figure 1 can be compactly written as

$$x_a^T = f[b_{rs}^t, O_r^t] + v_a^t \quad ……… \quad (4)$$

where
- x_a^t represents the observed traffic flows at link *a* during time interval *t*
- *f [.]* represents the dynamic mapping algorithm between OD flows and link traffic flows
- b_{rs}^t represents OD proportions between OD pair *r* and *s* departed its origin during time interval *t*
- O_r^t represents the origin flow between departed during time interval *t*
- v_a^t represents the measurement error of traffic flows at link *a* during time interval *t*

Note that OD flows can be derived from origin flows and OD proportions. Dynamic mapping (*f [.]*) composed of macroscopic traffic simulation model.

Though the approach is promising Pueboobpaphan considered only freeway OD parameter estimation, where no path choice exists. Moreover macroscopic traffic simulation model, well known for critics was not evaluated before embedding it into OD flow estimation algorithm.

Macroscopic traffic simulation models mostly based on hydrodynamic theory considering aggregate behavior of vehicles are potential to be applied for large network analysis and feedback estimation. Due to the inconsistency of underlying theory, macroscopic models were severely criticized by several researchers among them Daganzo's (1995) is the most radical one. Daganzo pointed out three vital facts which are receiving perception, behavior at bottlenecks and influence of human behavior to differentiate the fluid flow and traffic flow. The criticism further extended on possibility of deriving negative flow speeds under extreme traffic conditions.

The third issue is judging the state of the system during congested traffic flow by observing traffic density. With traffic flow alone it cannot be performed as the traffic flow is not monotonically mapped to traffic density. Pueboobpaphan (2007) suggested occupying flow speed for this purpose, monotonically map to traffic density.

The purpose of this paper is giving an introduction to an innovative real-time OD flow estimation algorithm for large traffic networks focusing on the aforesaid issues. The algorithm initiates with a set of origin flows and destination flows. Preliminary OD flows are computed with a traffic distribution model. It further suggests a dynamic mapping between link traffic flows and OD flows. Dynamic mapping composed of Probit model based stochastic traffic assignment to admit persisting path choices in network and a macroscopic model carefully selected from a performance evaluation study. Flow speed estimation will additionally be carried out by means of macroscopic model in parallel with link traffic flow estimation to judge the state of the system especially during congestion.

Finally feedback estimation is incorporated by means of unscented kalman filter (UKF) to maintain the consistency of estimation with real-time observations. Unscented kalman filter admits dynamic mapping process which simply cannot be tackled with standard kalman filter.

2. Joint estimation of OD flows and link flows

For the issues in OD flow estimation for large traffic networks discussed earlier, Kamide (2008) suggested a joint estimation technique combining the two conventional approaches described in section 1. Each approach was arranged in such a way to estimate preliminary OD flows and subsequently link traffic flows. The later indeed for the purpose of incorporating feedback estimation using actually observed link traffic flows. Note that the method is an extended version of Pueboobpaphan (2007) to cover large networks. Kamide's algorithm incorporated path choice behavior through two stage Logit model formulated from the data obtained from a questionnaire survey on drivers. Thus initiating the joint estimation algorithm with origin flows, preliminary OD flows and path flows were obtained by means of Logit models. Obtained path flows thereafter utilized to estimate link traffic flow by means of macroscopic model based simulation.

Kamide's algorithm seems prominent to treat large networks despite the fact that Logit models and macroscopic models are severely criticized by several researchers (Maher, 1997; Daganzo, 1995). Moreover the constraint (equation 2) concerning destination flow was ignored. Indeed it cannot be embedded if Logit model is in practice.

Large traffic networks are complicated with path overlapping phenomenon. To treat this problem influence of one path on the other should be accommodated in the model. However Logit model is incapable of capturing interrelationship between alternatives, hence path overlapping (Maher, 1998) cannot successfully be represented.

As a result of persisting shortcomings in the models, link traffic flow estimation is likely to be biased. Hence OD flow computation with feedback estimation becomes inefficient. We, therefore intend to eliminate the drawbacks in Kamide's algorithm by replacing the proposed models with efficient ones briefed in next section.

3. New proposal for joint OD flow estimation

The new method proposes a traffic distribution model and a traffic assignment model in place of two stage Logit model respectively. Furthermore macroscopic model, carefully chosen from a pre-evaluation study putting premium on the earlier criticisms is utilized for link traffic flow estimation.

(1) Traffic distribution

Traffic distribution in this study is subject to the information provided that, both the total flow generated at each origin (O_r^t) and the total flow attracted to each destination (D_s^t) are known and fixed represented in equations 1 and 2. It is reasonable assuming traffic flow is distributed according to the transportation cost between OD pairs. In the system point of view the total transportation cost of the system must be minimized, compactly written as

$$\min Z(q) = \sum_{j=1}^{m} \sum_{i=1}^{n} c_{ij}^t q_{ij}^t \qquad \text{……….(5)}$$

Where, c_{ij}^t and q_{ij}^t denote respectively the transportation cost and assigned OD flow between OD pair *ij*. By defining the transportation cost in terms of shortest travel time, a possible set of preliminary OD flows can be derived.

(2) Traffic assignment and link traffic flow estimation

Derived OD flows are then assigned to available paths between OD pairs with a stochastic assignment process. A well-known stochastic assignment technique, the method of successive averages (MSA) is adopted for this task. Though MSA suffers in defining prominent convergence criteria, it provides a straight forward algorithm that is easy to implement in a computer program. Given initial network flows, computation of the equilibrium link flows and hence path flows with MSA, forms an optimization problem that is solved iteratively. At each iteration the current path flows can be determined according to the path choice probabilities, and hence link flows are calculated. Macroscopic traffic simulation model is incorporated here for computing link flows. This enables the computation of improved link flows and costs and hence updated path costs. By knowing the updated path costs for the current step, the path flows for next step can be determined again according to the path choice probabilities.

Calculating path choice probabilities inevitably depends on driver's path choice behavior and overlapping of paths. The earlier one cannot simply be modeled as it is influenced by human behavior. Most of the past approaches thus defined path choice behavior using travel time only (Dial, 1971; Maher, 1998). By defining the utility of a path in terms of travel time Probit model which can take account of path overlapping or correlated paths is adopted for path choice probability calculation. Thus finally MSA incorporated with macroscopic model produces link traffic flows after the iteration process.

(3) Feedback estimation

Our goal in using feedback estimation is forming a relationship between link traffic flows and origin flows. Once correct origin flows are derived from feedback estimation. OD flows can simply be computed by means of traffic distribution model. Kalman filter is a popular tool for feedback process estimates the system state using an iterative two step approach, which are prediction step and update step.

Since the dynamic simulation procedure adopted in this model cannot be simply expressed in a closed analytical form, standard kalman filter cannot be applied. Well known extended kalman filter (EKF) to deal with nonlinear systems also fails to treat dynamic mapping. The unscented kalman filter (UKF), a new technique relies upon a mathematical technique referred to as the unscented transform is thus preferred for feedback estimation, which has the same computational effort as EKF but produces accurate results. UKF on the other hand permits the usage of any nonlinear dynamic mapping for both continuous and discontinuous transformation.

Figure 2 illustrates the newly proposed algorithm for real-time OD flow estimation.

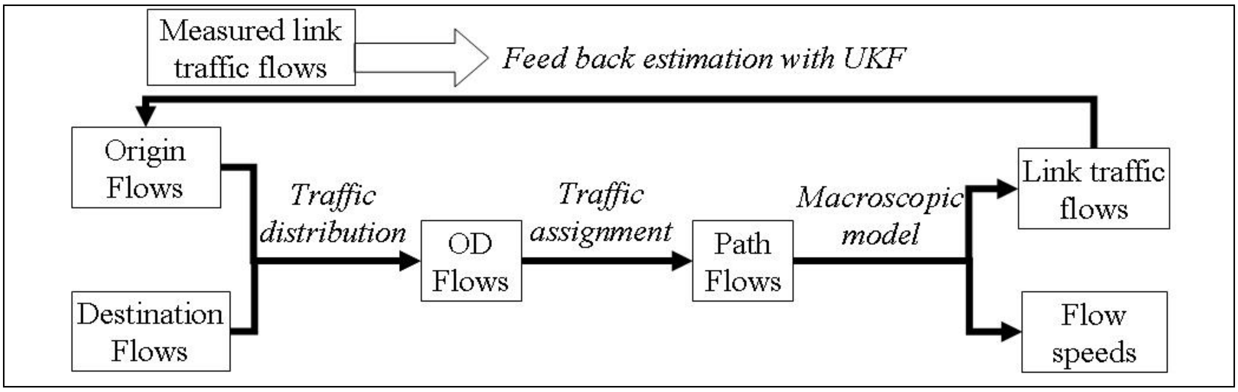

Figure 2 : Proposed real-time OD flow estimation algorithm

4. Summary

This paper proposes real-time OD flow estimation algorithm for large traffic networks using the combination of three models to deal with three vital issues. First issue is determination of vast number of unknown OD flows from limited data available tackled with traffic distribution model in deriving preliminary OD flows. Second issue is formulating a non-linear relationship between preliminary OD flows and link traffic flows in order to enable the comparison with actually observed link traffic flows. The non-linear relationship is formed though Probit model based stochastic traffic assignment and a macroscopic model. Third issue is congestion traffic flow analysis performed with flow speeds derived simultaneously with link traffic flows. In addition to that feedback estimation with unscented kalman filter is occupied to keep the consistency of estimation process with actual measurements.

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