附件一

行政院國家科學委員會補助專題研究計畫 □ 成 果 報 告 ☑期中進度報告

應用車輛辨識系統提昇起迄旅次矩陣推估之研究 (II/III)

Application of Automatic Vehicle Identification System to Enhance the Estimation of O-D Matrices (II/III)

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1.中文摘要

1.1 中文摘要

本計畫第二年期旨在結合格位傳遞理論（cell transmission model, CTM）及卡門濾波理論（extended Kalman filtering, EKF），提出一個整合型動態起迄矩陣反覆推估方法。其中，CTM為一中觀車流模擬方法，可用以精確且迅速地推估上匝道車流至目的地匝道之到達時間與分佈型態，並將其輸入 EKF 進行該時段之起迄矩陣推估。而推估所得之起迄矩陣則進一步再代入 CTM 重新模擬其到達型態，如此反覆以致收斂為止。

為驗證本模式之有效性與應用性，分別應用於簡例及實例(中山高北部路段)。結果顯示，在簡例驗證上，本模式可達到相當精確之成果，其RMSE可達0.0414。但在實例應用時，則RMSE值則較高，顯示仍存有相當程度之改善空間。基此，本計畫後續將進一步進行本演算法之改良，以作為下一研究年度進一步與車牌辨識系統結合之基礎。
關鍵字：動態起迄矩陣推估、格位傳遞模式、卡門濾波

1.2 Abstract

The second research year of this project aims to propose an integrated algorithm by hybridizing cell transmission model (CTM) and extended Kalman filtering (EKF) to estimate arrival distribution and O-D proportions respectively and iteratively. An exemplified example of a freeway corridor are used to investigate the capability of CTM in replicating traffic dispersion phenomenon. Results show that CTM can accurately capture the traffic dispersion under various traffic conditions. The degree of traffic dispersion gets large as traffic flow increases. To demonstrate the applicability of the proposed estimation algorithm, a case study of Taiwan No.1 Freeway is conducted. Results show that the proposed algorithm can estimate the O-D proportion with a low average RMSE of 0.0414. However, the results of the case study of a larger scale field case show that the RMSE values are high, leaving a lot of room for improvement. Thus, this project will continue to improve the proposed algorithm.
Keywords：*Dynamic origin-destination, Cell transmission model, Extended Kalman filtering*.

2. INTRODUCTION

Accurate dynamic origin-destination (O-D) information is required for the implementation of real-time traffic control measures, such as real-time route guidance and signal control. Numerous studies have devoted to developing estimation algorithms for the dynamic O-D matrix based mainly on observable mainline and ramp flow rates. The dynamic O-D matrices estimation algorithms can be divided into two categories (Ho, 2008): assignment-based (*e.g.* Ashok and Ben-Akiva, 2000, 2002) and non-assignment-based (*e.g.* Chang and Wu, 1994; Chang and Tao, 1996, 1999; Lin and Chang, 2005, 2007). The assignment-based method primarily relies on a dynamic traffic assignment algorithm to generate link flows; while the non-assignment-based method directly estimates O-D matrices. However, this issue remains challenging in that the number of parameters to be estimated is always far greater than the available information, thus additional assumption or exogenous information, such as route choice behaviors, priori O-D matrix information, sequence of observational periods of traffic counts data (e.g. Bell, 1983, 1991; Yang *et al.*, 1992, 1995; Vardi, 1996; Lo, *et al.*, 1996; Hazelton, 2001), should be further considered.

One of the most challenging issues remained to be tackled in the context of dynamic O-D matrices estimation is the impact of travel time variability on the time-varying O-D matrices. Chang and Wu (1994) assumed that the vehicles entering the freeway in a time interval are distributed in a small range (within two time intervals). However, if an O-D pair traffic traverses a sufficiently long distance or experiences moderate to heavy congestions, then the travel time variability may be rather large, which can result in a serious traffic dispersion phenomenon. As a result, the O-D pair traffic entering the freeway in a specific narrow time interval will reach their destinations over a wide time interval, which will greatly increase the difficulty in accurately estimating the dynamic O-D matrices. In other words, an accurate prediction model for the arrival distribution of entering O-D pair traffic under various traffic conditions is undoubtedly imperial for dynamic O-D matrices estimation.

Based on this, Chang and Tao (1995) assumed a macroscopic traffic model to efficiently predict the travel time according to concurrent traffic conditions and used the predicted travel time to estimate traffic arrival distributions and then to estimate the O-D matrices. Lin and Chang (2005, 2007) further assumed the travel time of drivers departing from *i* during time interval *k* to *j* following a certain distribution and then used such a distribution to estimate their arrival patterns. However, the studies of Chang and Wu (1994), Chang and Tao (1995) and Lin and Chang (2005, 2007) all made strong assumptions regarding the prediction of traffic dispersion, which might not be valid for various conditions from free-flow to gridlock. In addition, the state equations in the abovementioned studies may involve relatively too many parameters, largely increasing the model complexity to be implemented.

To efficiently and accurately capture the traffic behaviors along with their arrival distributions under various traffic conditions, this paper combines cell transmission model (CTM) and extended Kalman filtering (EKF) to simulate the traffic movement behaviors, to predict the arrival distributions of all O-D pair traffic in various time intervals, and then to estimate the dynamic OD matrices. CTM, proposed by Daganzo (1994), can efficiently simulate traffic hydrodynamics under various traffic conditions. Moreover, the conceptual representation of spatial (cell) and temporal (discrete time click) of traffic makes CTM especially suitable for dynamic O-D matrices estimation. Our proposed model not only results in a substantial increase of system observability with significantly less parameters than those in literature, but also contributes to enhance the quality of dynamic O-D matrices estimation.

The remainder of this paper is organized as follows. Section 2 gives the definitions of the problem, variables and related parameters. Section 3 presents the proposed cell-based arrival distribution prediction model. An exemplified freeway corridor with six interchanges is used to investigate the degree of traffic dispersion under traffic scenarios ranging from free-flow to congested flow conditions. Section 4 introduces the framework of the proposed algorithm. A case study is conducted in Section 5 to validate the applicability and performance of the proposed algorithm. Finally, concluding remarks and suggestions for future research follow.

3. PROBLEM DEFINITION

Consider a typical linear freeway corridor with *N* segments, coding 0 to *N*-1, as shown in Figure 1. Assume that detectors are installed at all on-ramps, off-ramps, and mainline links. The information that is readily available for estimation of dynamic O-D distribution is the time series of entering flow, $q_i(k)$, exiting flow, $y_j(k)$, and mainline flow, $U_l(k)$. The notations used in this paper are defined in Table 1.

Table 1 Definition of variables and parameters

Variables/ parameters	Definition
$q_0(k)$	The number of vehicles entering the upstream boundary of the freeway section during time interval *k*.
$q_i(k)$	The number of vehicles entering freeway from on-ramp *i* during time interval *k*, *i* = 1,2,. . . , *N* - 1.
$y_j(k)$	The number of vehicles leaving freeway from off-ramp *j* during time interval *k*, *j* = 1,2,. . . , *N* - 1.
$y_N(k)$	The mainline volume at the downstream end of the freeway section during time interval *k*.
$U_i(k)$	The number of vehicles crossing the upstream boundary of segment *i* during time interval *k*, *i* = 1,2,. . . , *N* - 1.
$T_{ij}(k)$	The number of vehicles entering the freeway from on-ramp *i* during time interval *k* that are destined to off-ramp *j*, where $0 \le i < j \le N$.
t_0	The length of one unit time interval.
$b_{ij}(k)$	The proportion of $q_i(k)$ heading toward destination node *j* during time interval *k*.
$\rho_{ij}^{m}(k)$	The fraction of $T_{ij}(k\text{-}m)$ vehicles departing from entry node *i* during time interval *k* that takes *m* time intervals to exiting node *j*.
$\rho_{ilj}^{m}(k)$	The fraction of $T_{ij}(k\text{-}m)$ trips from entry node *i* during time interval *k* that takes *m* time intervals to mainline node.

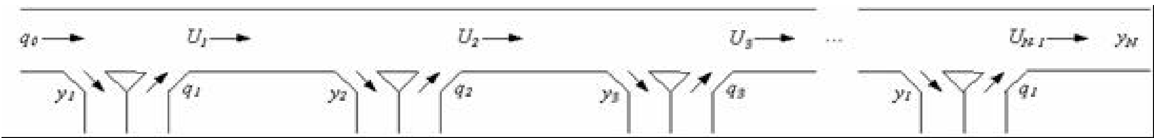


Figure 1 A typical linear freeway corridor

The relation between the dynamic O-D pattern and resulting link flow can be expressed by equations (Lin and Chang, 2007):

$$q_i(k) = \sum_{j=i+1}^{N} T_{ij}(k), \qquad i = 0,1,..., N-1 \tag{1}$$

$$T_{ij}(k) = q_i(k) \cdot b_{ij}(k), \qquad 0 \le i < j \le N \tag{2}$$

The above two equations are subjected to the following natural constraints:

$$0 \le b_{ij}(k) \le 1, \qquad 0 \le i < j \le N \tag{3}$$

$$\sum_{j=i+1}^{N} b_{ij}(k) = 1 \qquad i = 0,1,2,...N-1 \tag{4}$$

Consider the speed variation among drivers, it is reasonable to assume that the travel time of vehicles from node *i* to node *j* during time interval *k* are distributed among time intervals *k*-*M*,…, *k*-1, and *k* where *M* is the maximum number of intervals required for vehicles to traverse the entire freeway section. The traffic volume leaving freeway from off-ramp *j*, $y_j(k)$, can thus be expressed as

$$y_j(k) = \sum_{m=0}^{M} \sum_{i=0}^{j-1} \; q_i(k-m) \cdot \rho_{ij}^{m}(k) \cdot b_{ij}(k-m) \tag{5}$$

$$U_l(k) - q_l(k) = \sum_{m=0}^{M}\sum_{i=0}^{j-1}\sum_{j=l+1}^{N}\left[q_i(k-m)\rho_{il}^{m}(k)\right]b_{ij}(k-m) \tag{6}$$

where $\rho_{ij}^{m}(k)$ shall satisfy the following relations:

$$0 \le \rho_{ij}^{m}(k) \le 1, \quad 0 \le i \le j \le N, \quad m = 0,1,\ldots,M \tag{7}$$

$$\sum_{m=0}^{M}\rho_{ij}^{m}(k+m) = 1, \ \ 0 \le i < j \le N \tag{8}$$

Obviously, the system formulation has a large number of state parameters, *i.e.*, $b_{ij}(k)$ and $\rho_{ij}^{m}(k)$. The number of these unknown parameters increases with the necessary M value. As such, some more information is required to ensure this proposed model to be computationally efficient and tractable.

To deal with the large number of unknown parameters, Chang and Wu (1994) simplified the formulations by assuming that the speeds of vehicles entering the freeway at the same time interval are distributed in a small range. Therefore, Eqs. (5) and (6) can be rewritten as

$$y_j(k) = \sum_{i=0}^{j-1}\left[q_i(k - t_{ij}^{+}(k))\right]\theta_{ij}^{+}(k)b_{ij}(k - t_{ij}^{+}(k))) + \sum_{i=0}^{j-1}\left[q_i(k - t_{ij}^{-}(k))\right]\theta_{ij}^{-}(k)b_{ij}(k - t_{ij}^{-}(k))) \tag{9}$$

$$U_l - q_l(k) = \sum_{i=0}^{l-1}\sum_{j=l+1}^{N}\left[q_i(k - t_{ij}^{+}(k))\right]\theta_{ij}^{+}(k)b_{ij}(k - t_{ij}^{+}(k))) + \sum_{i=0}^{j-1}\left[q_i(k - t_{ij}^{-}(k))\right]\theta_{ij}^{-}(k)b_{ij}(k - t_{ij}^{-}(k))) \tag{10}$$

By simplifying the formulation as Eqs. (9) and (10), the number of unknown parameters reduces from $(M + 1)N(N + 1)/2$ to $3N(N + 1)/2$. However, if the target freeway corridor is sufficiently long and experiences moderate congestion, the speeds of vehicles for the same O-D may vary in a wide range. Then, Eqs. (9) and (10) are not adequate for capturing all complex interrelations between traffic flows and O-D patterns. To deal with these limitations, Lin and Chang (2005) proposed a new set of generalized formulations by employing a distribution to represent the potential variation of travel times among drivers due to the impact of congestion and due to the difference in their desired speeds. They assumed that the travel time of drivers departing from node i during time interval k to node j follow a specific distribution. Since the travel times for the same O-D pair drivers departing during the same time interval follow a distribution, Lin and Chang (2005) replaced $\rho_{ij}^{m}(k)$ with a cumulative density function for one time interval as follows:

$$\rho_{ij}^{m}(k) = \int_{m\cdot t_0}^{(m+1)t_0} f_{ij}^{m}(x)dx \tag{11}$$

By applying the above travel time distribution concept, the relationships between ramp volumes and O-D proportions can be rewritten as:

$$\begin{aligned} y_j(k) &= \sum_{m=0}^{M}\sum_{i=0}^{j-1} q_i(k-m)\cdot\rho_{ij}^{m}(k)\cdot b_{ij}(k-m) \\ &= \sum_{m=0}^{M}\sum_{i=0}^{j-1} q_i(k-m)\cdot\left[\int_{m\cdot t_0}^{(m+1)t_0} f_{ij}^{m}(x)dx\right]\cdot b_{ij}(k-m) \end{aligned} \tag{12}$$

$$U_l(k) - q_l(k) = \sum_{m=0}^{M}\sum_{i=0}^{j-1}\sum_{j=l+1}^{N}\left[q_i(k-m)\rho_{il}^{m}(k)\right]b_{ij}(k-m)$$

$$= \sum_{m=0}^{M}\sum_{i=0}^{j-1}\sum_{j=l+1}^{N} q_i(k-m)\left[\int_{m\cdot t_0}^{(m+1)t_0} f_{ij}^{m}(x)dx\right]b_{ij}(k-m) \qquad (13)$$

Compared to Chang and Wu (1994), the number of unknown parameters for Eqs. (12) and (13) has reduced from 3N(N + 1)/2 to 2N(N + 1)/2. On the other hand, Lin and Chang (2005) represented the different speeds of vehicles for the same O-D pair with a distribution of travel time.

Although the relevant studies (e.g. Chang and Wu, 1994; Chang and Tao, 1995; Lin and Chang, 2005, 2007) have shed light on the dynamic OD matrices estimation, most of them made subjectively assumptions regarding arrival distributions, which may not be valid for various conditions from free-flow to gridlock. In addition, most of these models are too complex, causing low efficiency in estimation. In view of the importance of the arrival distribution prediction and the estimation efficiency required for real-time implementation, this study aims to develop a model that can accurate capture the traffic hydrodynamics under various traffic conditions in an efficient manner.

4. CELL-BASED ARRIVAL DISTRIBUTION MODELING

The present paper employs CTM to predict the arrival distribution of an O-D pair traffic, which will then be used to compute $\rho_{ij}^{m}(k)$.

4.1 Cell Transmission Model

As shown in Figure 2, a freeway is equally discretized into homogeneous sections (cells), numbered consecutively from i = 1 to I starting with the upstream end of the road, where the length of each cell is the distance traveled by a vehicle in one clock tick under light traffic.

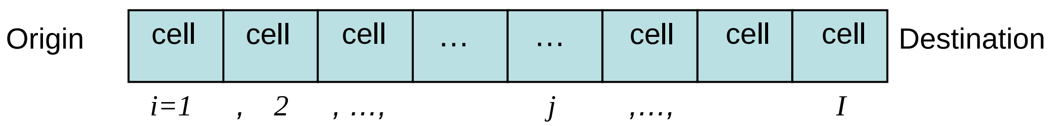


Figure 2 Cell representation of a freeway corridor

In light traffic, all vehicles in a cell can be assumed to advance to the next cell with each click. It is unnecessary to know where within the cell they are located. Therefore, the system's evolution obeys:

$$n_{i+1}(t+1) = n_i(t) \qquad \text{for } t = 0, 1, 2, \ldots, T \qquad (13)$$

where $n_i(t)$ is the number of vehicles in cell i at time t. It is assumed that this equation holds true for all traffic flows unless queuing occurs. The following two variables are introduced to incorporate queuing in the model: (1) $Q_i(t)$, the maximum flow from cell i – 1 to i during time interval t (when the clock advances from t to t + 1), also known as "capacity," and (2) $N_i(t)$, the maximum number of vehicles that can be present in cell i in time t. Thus, $N_i(t) - n_i(t)$ is the amount of empty space in cell i at time t.

The CTM assumes a simplified version of the fundamental diagram, usually based on a trapezium form, as shown in Figure 3, and provides simple solutions for realistic networks. It is assumed that a free-flow speed v at low densities and a backward shockwave speed w for high densities are constant ($v \geq w$).

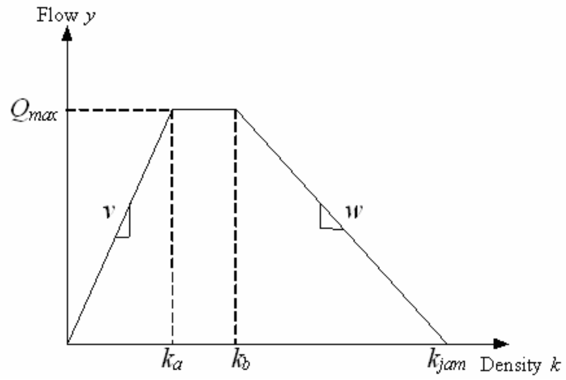


Figure 3 Fundamental diagram of CTM

With these, we define $y_i(t)$ as the number of vehicles that can flow into i for time interval t as:

$$y_i(t) = \min\{n_{i-1}(t)\ ,\ Q_i(t)\ ,\ \frac{w}{v}[N_i(t) - n_i(t)]\} \tag{14}$$

The CTM is based on a recursion where the cell occupancy at time t + 1 equals its occupancy at time t, plus its inflow and minus the outflow:

$$n_i(t+1) = n_i(t) + y_i(t) - y_{i+1}(t) \tag{15}$$

If the remaining storage capacity and flow capacity of next cell is sufficient, all vehicles will move forward to the next cell; otherwise, only part of them can move proportionally, the logic is as:

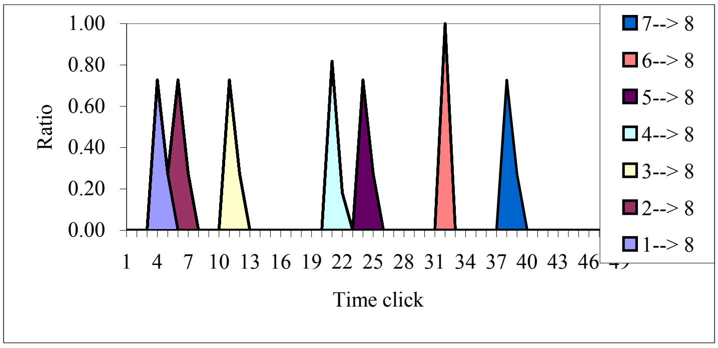
$$\begin{aligned} &\textit{if} \quad y_i(t+1) + r_i(t+1) \leq \min[Q_i(t+1), N - n_i(t+1)] \\ &\textit{then} \quad Q_{i+1}(t+1) = y_i(t+1) + r_i(t+1) \end{aligned} \tag{16}$$

$$\begin{aligned} &\textit{if} \quad y_i(t+1) + r_i(t+1) > \min[Q_i(t+1), N - n_i(t+1)] \\ &\textit{then} \quad Q_{i+1}(t+1) = 1 - \left[\min[Q_i(t+1), N - n_i(t+1)] \Big/ y_i(t+1) + r_i(t+1)\right] \end{aligned} \tag{17}$$

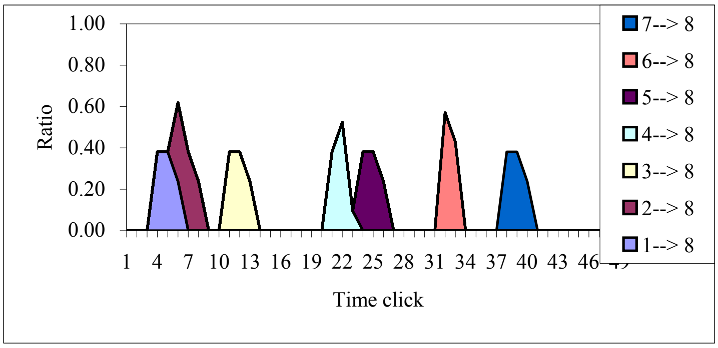
4.2 Replicating Traffic Dispersion Phenomenon

To demonstrate the capability of CTM in replicating the traffic hydrodynamics and to investigate the degree of traffic dispersion under various traffic conditions, a simulation on a three-lane freeway section with eight interchanges has been conducted. Parameters are set as follows: free flow speed=120 km/hr, jam density=125 vehicles per kilometre per lane, capacity=7,200 vehicles per hour, cell storage capability=375 vehicles, time click=30 seconds, and cell length=1 km.

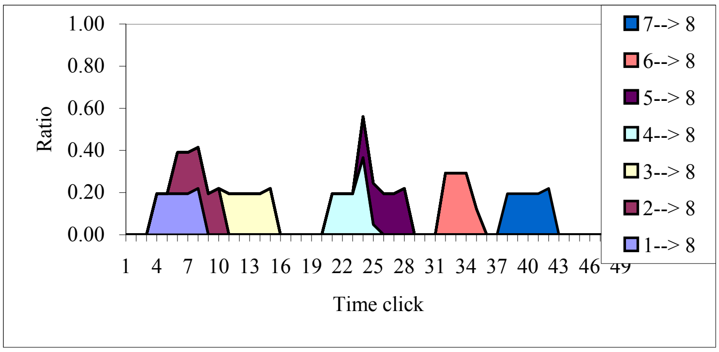
Four scenarios with various traffic conditions are simulated, including free-flow, light synchronized flow, heavy synchronized flow and congested flow. Taking the traffics entering at seven interchanges (No.1 to No.7) and heading to No.8 interchange in time interval t=1 for example, their arrival distributions under various traffic conditions are graphically depicted in Figure 4. As shown in Figure 4 (a), almost all traffics arrive at No.8 interchange within one or two time intervals under free-flow condition. Once the traffic flow increases, the degree of traffic dispersion will significantly appear. As shown in Figures 4(b)-(d), the same entering traffic will arrive at No.8 interchange among a wider range of time intervals ranging from two to three time intervals under light synchronized flow, four to five time intervals under heavy synchronized flow, and six to eight time intervals under congested flow, suggesting the capability of the CTM model in replicating traffic dispersion phenomenon.



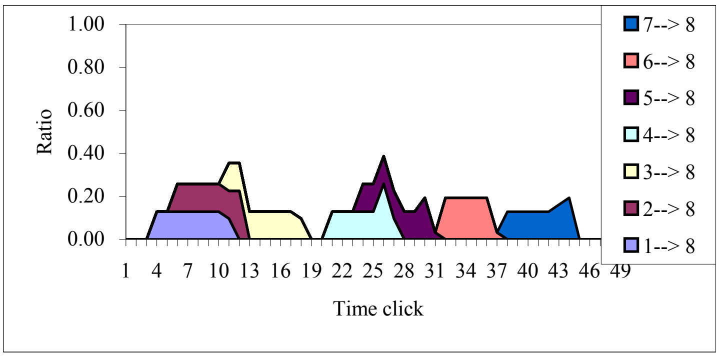
(a) Free-flow



(b) Light synchronized flow



(c) Heavy synchronized flow



(d) Congested flow

Figure 4 Distributions of No.8 interchange arrival traffics from various origins

5. THE PROPOSED ESTIMATION ALOGRITHM

5.1 Model Framework

To replicate traffic behaviors by CTM, traffic demand of each OD pair has to be given in advance. That is, a set of $b_{ij}(k)$ has to be determined and used to assign the detected on-ramp traffics to different downstream interchanges. Once the arrival distributions of all entering traffic have been successfully simulated, $\rho_{ij}^{m}(k)$ can be computed and used to calibrate the O-D proportions of entering traffic $q_i(k)$ by EKF, namely $b_{ij}'(k)$. Then, the new O-D proportions $b_{ij}'(k)$ will be used to replicate a revised arrival distribution $\rho_{ij}^{m}{}'(k)$ in an iterative manner. The proposed algorithm for estimating dynamic O-D matrices is depicted in Figure 5.

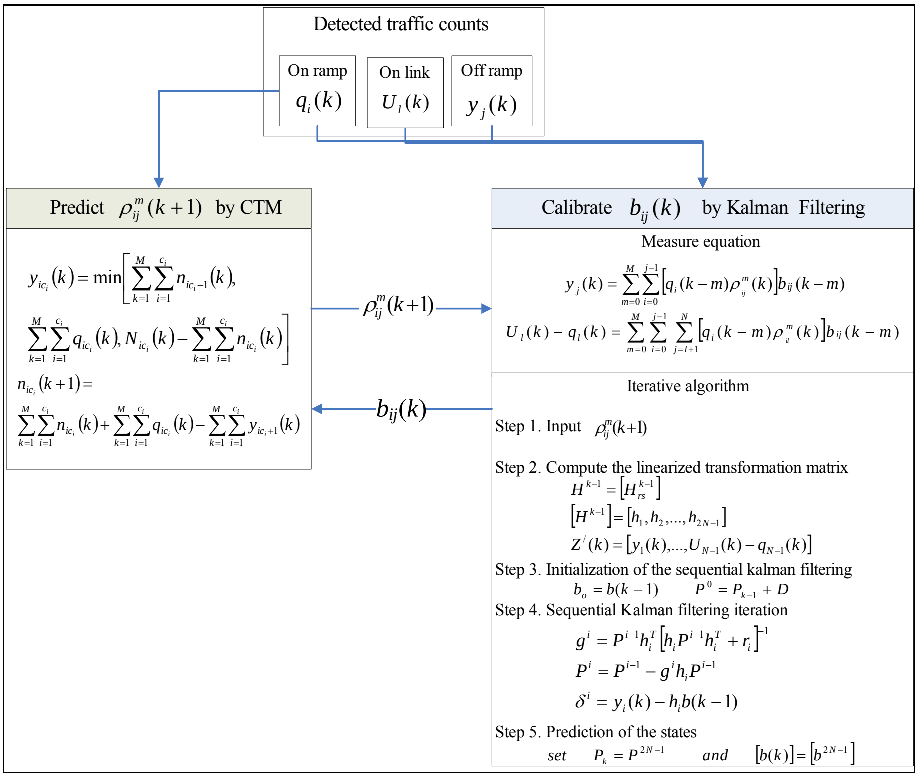


Figure 5 Framework of the proposed algorithm

In the above model formulation, the information of each O-D pair can be estimated using the data provided by the surveillance system or historical information, and the unknown set of parameters are O-D proportions, $b_{ij}(k)$.

As used in most existing approaches, the dynamic O-D parameters, $b_{ij}(k)$, are assumed to follow the random walk process between successive time intervals:

$$b_{ij}(k+1) = b_{ij}(k) + w_{ij}(k), \quad 0 \le i < j \le N \tag{18}$$

$$B(k+1) = B(k) + W(k) \tag{19}$$

$$Z(k) = H(k) \cdot B(k) + W(k) \tag{20}$$

$$Z(k) = \left[y_1(k), y_2(k), \ldots, y_N(k); U_1(k) - q_1(k), \ldots, U_{N-1}(k) - q_{N-1}(k)\right]^T \tag{21}$$

where, $w_{ij}(k)$, a random term, is an independent Gaussian white noise sequence with zero mean and its covariance, $Z(k)$, is a column vector, $H(k)$ is a matrix with its entries given by the corresponding coefficients in Eqs. (12) and (13), and $e(k)$ is an observation noise vector, which can be defined as a Gaussian white noise with zero mean and its covariance matrix, and R = Var[$e(k)$] = diag[r_1, . . . , r_{2N-1}] is a diagonal positive definite matrix. $B(k)$ is a matrix of the O-D proportions of entering flows $b_{ij}(k)$. $W(k)$ is a matrix of white noise $w_{ij}(k)$.

The proposed estimation algorithm, based on the extended Kalman filtering concept, is presented as follows.

Step 0: Initialization.

Parameters settings include cell length L_i , i = 0,1,. . . , N-1, time interval, t_0. $\mathrm{var}[e(k)] = diag[r_1, r_2 ...]$. $X(0) = E[b(0)]$. $P(0) = Var[b(0)]$. Besides, on-ramp, link and off-ramp flows are given.

Step 1: Determine $\rho_{ij}^m(k)$ by CTM.

Step 2: Compute the linearized transformation matrix based on the determinant $\rho_{ij}^m(k)$.

$$H^{K-1} = [H_{rs}^{k-1}]$$

$$H_{j,Ni+j-i(i+1)}^{k} = \sum_{m=0}^{M} q_i(k-m) \cdot \rho_{ij}^m(k) \qquad for \quad 0 \le i < j \le N$$

$$H_{N+l,Ni+j-i(i+1)}^{k} = \sum_{m=0}^{M} q_i(k-m) \cdot \rho_{ij}^m(k) \qquad for \quad 0 \le i < j \le N$$

$$[H^{K-1}] = [h_1, h_2, ..., h_{2N-1}]^T$$

$$Z'(k) = [y_1(k), y_2(k), ..., y_N(k); U_1(k) - q_1(k), ..., U_{N-1}(k) - q_{N-1}(k)]^T$$

Step 3: Initialization of the sequential Kalman filtering method.

set $b_0 = b(k+1)$

$p_0 = p_{k+1} + D$ where $D = [d_b, ..., d_b]$ is a covariance matrix of $W(k)$

Step 4: Sequential Kalman filtering iterations.

For i = 1, 2, …, 2N-1

$$g^i = p^{i-1} h_i^T [h_i p^{i-1} h_i^T + r_i]^{-1}$$

$$p^i = p^{i-1} - g^i h_i p^{i-1}$$

$$\delta^i = y_i(k) - h_i b(k-1)$$

Truncation:

$$\alpha' = \underset{0 \le \alpha \le 1}{MAX} [\alpha | 0 \le [b^{i-1}] + \alpha \delta^i g^i \le 1]$$

Set $[b^i] = [b^{i-1}] + \alpha \delta^i g^i$

Normalization:

For m=1, 2, …, N-2

$$\beta_m = \sum_{j=m+1}^{N} b_{mj}^i$$

$$b_{mj}^i = b_{mj}^i \big/ \beta_m \qquad j = m+1, \ldots, N.$$

Step 5: Stop condition test.

Check the convergence of estimated O-D proportions. If preset stop conditions (convergence level or number of iterations) has not been met, then go to Step 1. Otherwise, go to Step 6.

Step 6: Prediction of the states.

Set $p_k = p^{2N-1}$ and $[b(k)] = [b^{2N-1}]$, $k = k + 1$, go to Step 1.

6. CASE STUDY

To demonstrate the performance and applicability of the proposed estimation algorithm, a section of Taiwan No.1 Freeway (Taishan toll station to Yangmei toll station) is studied. This is a 36 km three-lane freeway section with 6 interchanges containing 28 O-D pairs, as shown in Figure 6.

To generate real time-dependent traffic flows, the time series of four hours O-D traffics under different traffic conditions are given. Based on the assumed O-D pair flows, DynaTaiwan, a traffic simulation software modified from DynaSmart to account for the traffic behaviors in Taiwan, is used to generate real-time on-ramp, link, and off-ramp traffic flows at every 30-second time click. The three simulated real-time detected traffic flows are then inputted into the proposed estimation algorithm.

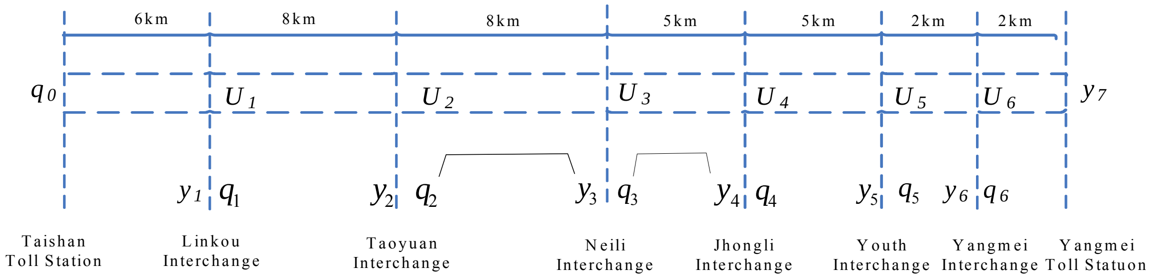


Figure 6 Northern section of Taiwan No.1 Freeway

The deviation of the estimated O-D proportions of each time click and each O-D pair from given O-D proportions is used as a measure of model performance. The root-mean-square error (RMSE) is used to evaluate the performance of the proposed algorithm, which is defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\sum_{k=1}^{T}(b_{ij}(k)-\hat{b}_{ij}(k))^2}{N(N-1)T}} \quad (22)$$

where, $\hat{b}_{ij}(k)$ is the estimated O-D proportions of traffic entering interchange i and heading to interchange j.

To investigate the effects of initial value settings of O-D proportions on the performance of the proposed algorithm, two initial value setting approaches are adopted and compared: randomly generated (RG) approach and equal share (ES) approach. Take origin No.4 interchange as an example, the associated O-D proportions are denoted as $b_{45}(k)$, $b_{46}(k)$, and $b_{47}(k)$. For the RG approach, three random numbers 0.123, 0.341, and 0.782 are generated and then normalized such that the sum of three proportions equals 1. Thus, $b_{45}(k)$=0.099, $b_{46}(k)$=0.274, and $b_{47}(k)$=0.628. In contrast, for the ES approach, three proportions for the same example is simply set as $b_{45}(k)$=0.333, $b_{46}(k)$=0.333, and $b_{47}(k)$=0.334.

The distributions of real b_{15} proportions (from Linkou interchange to Youth interchange) along with estimated O-D proportions by RG and ES approaches are given in Figure 7. Note that the proposed algorithm can predict real O-D proportions accurately regardless which initial value setting approaches being adopted. However, the predicted result by RG approach is slightly superior to that by ES approach. Thus, the RG approach will be adopted in predicting other O-D proportions.

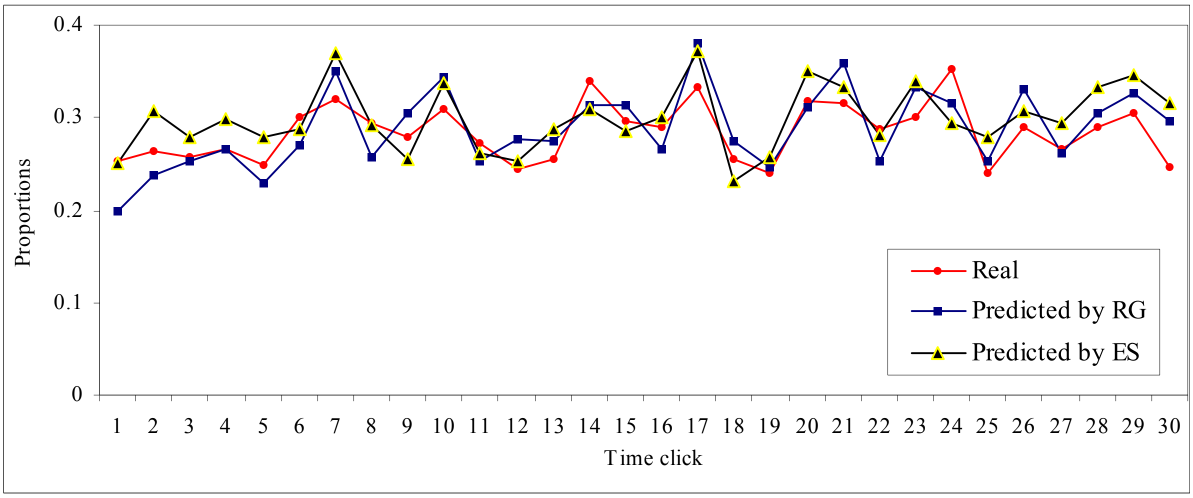


Figure 4 Distributions of real and two predicted b_{15} proportions by EG and ES approaches

Table 5 reports the RMSE values of 28 O-D proportions of the proposed integrated algorithm. Results show that the overall average *RMSE* is 0.0414, indicating a rather good fitness of the proposed algorithm. The applicability of the proposed algorithm has been proven.

Table 5 RMSE values of the proposed algorithm of the case study

From \ To	Linkou interchange	Taoyuan interchange	Neili interchange	Jhongli interchange	Youth interchange	Yangmei interchange	Yangmei toll station
Taishan toll station	0.0399	0.0435	0.0337	0.0197	0.0201	0.0202	0.0258
Linkou interchange	-	0.0361	0.0463	0.0411	0.0441	0.0438	0.0404
Taoyuan interchange	-	-	0.0502	0.0398	0.0289	0.0376	0.0444
Neili interchange	-	-	-	0.0471	0.0359	0.0426	0.0419
Jhongli interchange	-	-	-	-	0.0439	0.0305	0.0612
Youth interchange	-	-	-	-	-	0.0739	0.0688
Yangmei interchange	-	-	-	-	-	-	0.0698

7. CONCLUDING REMARKS

This paper has developed an integrated estimation algorithm by combining cell transmission model (CTM) and extended Kalman filtering (EKF) to respectively and iteratively estimate the arrival distribution and the O-D proportions. Our results from an exemplified example of a freeway corridor have shown that CTM can surely capture the traffic dispersion under various traffic conditions. The degree of traffic dispersion will get enlarged as traffic flow increases. The results from a case study on Taiwan No.1 Freeway have also shown that the proposed algorithm can accurately estimate the O-D proportions with a low RMSE of 0.0414. The applicability of the proposed integrated algorithm has been proven.

Several directions for future research can be identified. First, the applicability and efficiency of the proposed algorithm on a large scale network should be further examined. Second, due to data availability in the case study, the O-D matrices are arbitrarily given and then used to generate "real time" detected traffic flows by traffic simulation software, DynaTaiwan. However, with advanced traffic surveillance technologies, it is feasible to collect real time traffic information in the future study to further examine the applicability of the proposed algorithm. Third, the proposed algorithm is only valid for the case of linear freeway corridor. In the future study, route choice behaviors should be incorporated to the proposed algorithm to suit for more complicated networks. Fourth, the estimation accuracy of the proposed algorithm under various traffic conditions also deserves further investigation and comparison. Last but not least, comparisons with other algorithms should also be conducted to demonstrate the superiority of the proposed algorithm.

8. 計畫成果自評

本計畫為三年期計畫。本年期所列之主要工作項目，預期之研究成果如下：

1.蒐集 AVI 系統辨識車輛之歷史資料

為分析及探討 AVI 所辨識車輛之行徑資料，本研究擬蒐集其歷史資料，並利用統計分析技術，如卡方檢定及判別分析，以探討各用路人使用道路之習慣。

2.建立 AVI 系統辨識車輛之預測模式

在進行動態起迄旅次矩陣預測時，由於 AVI 所辨識車輛之部份行徑資料必須加以進一步推估及判斷，方能據以建立有效之流量方程式。基此，本研究擬利用巨觀車流模式（traffic stream model）及灰預測模式進行短期車輛推移之模擬，再進一步利用 AVI 歷史資料，依據其車型、自用或營業用、使用時段及行駛路段，利用存活理論建立其通過其他座 AVI 系統之「存活」預測模型。

3.灰預測模式

本研究擬利用灰預測模式（grey prediction model, GM）建立「車輛推移之預測模組」時，俾能在有限資料下，提供短期交通資訊之預測。

4. 建立動態起迄旅次矩陣之推估模型

動態起迄旅次矩陣推估方法甚多，如貝氏推論法、卡門濾波法等。本研究將比較各方法在本課題之適用狀況及績效表現，再據以選擇最適用之方法。

上述第 1 及 2 項研究成果，於本年期研究過程中，發現以巨觀車流模式進行推估將導致相當大之誤差。因此，已改採中觀車流模式之格位傳遞模式（CTM）進行推估。而本研究成果也驗證此一方法之精確度與可行性。至於灰預測模式已於之前研究中完成，並已發表。將於下一年度進一步加以整合。因此，本年期主要研究成果為第 4 項研究內容，並已順利達成。此外，本計畫之主要成果已分別發表國際研討會 2 篇文章[18, 20]、國內研討會 1 篇學術論文[17]，並已改寫投稿學術期刊中[19, 20]。此外，本計畫亦用以指導兩名碩士生進行論文寫作[21, 22]及一名博士生進行論文寫作[23]，其中碩士生均已順利畢業。

9. REFERENCES

1. Bell, M.G.H. (1983) The estimation of an origin-destination matrix from traffic counts, **Transportation Science 17**, 198-217.
2. Bell, M.G.H. (1991) The estimation of origin-destination matrices by constrained generalized least squares, **Transportation Research 25B**, 13-22.
3. Hazelton, M. (2001) Inference for origin-destination matrices: Estimation, prediction and reconstruction, **Transportation Research 35B**, 667-676.
4. Lo, H., Zhang, N. and Lam, W. (1996) Estimation of an origin-destination matrix with random link choice proportions: A statistical approach, **Transportation Research 30B**, 309-324.

5. Vardi, Y. (1996) Network tomography: Estimating source-destination traffic intensities from link data, **Journal of the American Statistical Association 91**, 365-377.
6. Yang, H. (1995) Heuristic algorithms for the bilevel origin-destination matrix estimation problem, **Transportation Research 29B**, 231-242.
7. Yang, H., Sasaki, T., Iida, Y. and Akiyama, T. (1992) Estimation of origin-destination matrices from link traffic counts on congested networks, **Transportation Research 26B**, 417-434.
8. Ashok, K. and Ben-Akiva, M. (2000) Alternative approaches for real-time estimation and prediction of time-dependent original-destination flows, **Transportation Science 34**, 21-36.
9. Ashok, K. and Ben-Akiva, M. (2002) Estimation and prediction of time-dependent original-destination flows with a stochastic mapping to path flows and link flows, **Transportation Science 36**, 184-198.
10. Chang, G.L. and Tao, X. (1996) Estimation of dynamic network O-D distribution, **Proceedings of 13th Symposium on Transportation and Traffic Flow Theory**, Elsevier Science.
11. Chang, G.L. and Tao, X. (1999) An integrated model for estimating time-varying network O-D distribution, **Transportation Research 33A**, 381-399.
12. Chang, G.L. and Wu, J. (1994) Recursive estimation of time-varying origin-destination distributions with dynamic screenline flows, **Transportation Research 34B**, 277-290.
13. Daganzo, C.F. (1994) The cell transmission model: A dynamic representation of highway traffic consistent with the hydrodynamic theory, **Transportation research 28B**, 269-287.
14. Lin, P.W. and Chang, G.L. (2005) A robust model for estimating freeway dynamic origin-destination matrix, **Transportation Research Record 1923**, 110-118.
15. Lin, P.W. and Chang, G.L. (2007) A generalized model and solution algorithm for estimating dynamic freeway origin-destination matrix, **Transportation Research 41B**, 554-572.
16. Ho, W.M. (2008) **Comparisons of Assignment-based and Non-assignment-based Time Dependent O-D Estimation Models for General Networks.** Unpublished thesis, National Cheng Kung University (in Chinese).
17.邱裕鈞、艾嘉銘、范智超（2005），「用於起迄交通量預估之車牌辨識系統區位規劃問題」，2005道路交通安全與執法國際研討會，中央警察大學，第403-414頁，桃園縣，9月29日。
18.Chiou, Y.C. Fan, C.C. and L.W. Lan (2006) "A location selection model of license plate recognition system for enhancing the estimation of freeway O-D matrix," presented at the 11st *International Conference for Hong Kong Society of Transportation Studies*, Hong Kong, Dec.10~12.
19.Chiou, Y.C. and Fan, C.C. (2007) "Optimal locations of license plate recognition systems for freeway origin-destination matrix estimation," submitted to *Journal of Advanced Transportation*. (Under review)
20.Chiou, Y.C., Lan, W.L. and Tseng, C.M. (2009) "Estimation of dynamic freeway origin-destination matrices with cell-based arrival distribution modeling," submitted to *Journal of Eastern Asia Society for Transportation Studies.* (*Under review*)
21.范智超，「高速公路起迄旅次矩陣推估之研究」，逢甲大學交通工程與管理學系，碩士論文，民國95年。
22.許珮珊，「高速公路動態起迄旅次矩陣推估之研究」，交通大學交通運輸研究所，碩士論文，民國97年。
23.曾群明，「應用車牌辨識系統提昇動靜態起迄矩陣推估之研究」，交通大學交通運輸研究所，博士論文（進行中），民國97年。