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A Probability-Based Analytical Model Based on Deep Learning for Traffic Information Estimation

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***Abstract*—This paper proposes a probability density function model based on deep learning to analyze the relationships between the number of call arrivals and vehicle speed. Furthermore, a vehicle speed estimation method based on deep learning is proposed to estimate vehicle speed in accordance with the number of call arrivals. A traffic flow estimation method is proposed to estimate traffic flow in accordance with the number of normal location updates. Finally, a traffic density estimation method is proposed to estimate the traffic density in accordance with the estimated vehicle speed and the estimated traffic flow. In experiments, the simulation results showed that the accuracies of estimated vehicle speed and estimated traffic density are 96.36% and 96.45%, respectively.**

***Index Terms*—probability-based analytical model, intelligent transportation system, cellular floating vehicle data, traffic information estimation, deep learning**

I. Introduction

In recent years, because of advance in science and technology and the maturity of hardware, the intelligent transportation system (ITS) is becoming more and more powerful. Real-time traffic information, such as traffic flow, traffic density and vehicle speed, plays a significant role in ITS. Thus, many researchers contribute into enhancing the effectiveness of traffic information system and many research products have been published.

Traditionally, the methods of gathering real-time traffic information can be divided into three categories: vehicle detectors (VDs), global position system (GPS)-based probe cars, and cellular floating vehicle data (CFVD). Compared with other two methods, CFVD is characterized by low cost and large data volume and can avoid privacy issues [1]. This method makes use of tracking the movements of mobile stations (MSs) to estimate traffic information through cellular network signals (e.g., normal location update (NLU), handover (HO) and call arrival (CA)) [1].

The objectives of this study are summarized as follows.

1) A probability density function model based on deep learning is proposed to measure the relationships between the number of CAs and vehicle speed.
2) A vehicle speed estimation method based on deep learning is proposed to obtain the estimated vehicle speed in accrodance with the number of CAs.
3) A traffic flow estimation method is proposed to obtain the estimated traffic flow in accrodance with the number of normal location updates.
4) A traffic density estimation method is proposed to obtain the estimated traffic density in accrodance with the estimated vehicle speed and the estimated traffic flow.

II. Traffic Information Estimation

A. Vehicle Speed Estimation

This study adopts the number of CAs to estimate vehicle speed. As shown in Fig. 1, a MS in the car moving along the road performs the first call set-up (at time t_0) and then enters $Cell_i$ coverage (at time t_1). It subsequently performs the second call set-up (at time t_2) before leaving $Cell_i$ coverage (at time t_3). The proposed probability density function model and the proposed vehicle speed estimation method are presented as following subsections.

1) A Probability-Based Analytical Model for the Analysis of the Number of CAs and Vehicle Speed: The relationships between the number of CAs and traffic information were modelled in accrodance with probability functions, and the distribution of call inter-arrival time was assumed as an exponential distribution [1]. However, the practical distribution of call inter-arrival time may be not an exponential distribution. Therefore, this study uses deep learning techniques and adopts the cumulative distribution functions (CDFs) of exponential distribution, normal distribution and log-normal distribution to learn the CDF of call inter-arrival time. The call inter-arrival time is adopted as the input of neural network, and the CDF is adopted as the output of neural network. Furthermore, the differential learned neural network model denotes as the probability density function of call inter-arrival time [2]. The relationships between the number of CAs and vehicle speed can be expressed as Equation (1).

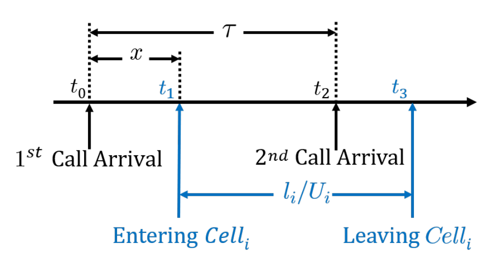

Fig. 1. The timing diagram for vehicle movement and CA on the road

The notations in this study are listed as follows.

- The practical vehicle speed, traffic flow and traffic density of $Cell_i$ are denoted as U_i, Q_i and K_i.
- The estimated vehicle speed, traffic flow and traffic density of $Cell_i$ are denoted as u_i, q_i and k_i.
- The number of CAs of $Cell_i$ is denoted r_i.
- The parameters μ_1, μ_2, μ_3, σ_2 and σ_3 are the weights of the proposed activation functions in the neural network.

$$
\begin{aligned}
r_i &= Q_i \times \Pr\left[t_1 < t_2 < t_3\right] \\
&= \mu_1 \times \left(1 - e^{-\frac{1}{\mu_1}\left(\frac{l}{u_i}\right)}\right) + \frac{l}{2u_i} \\
&- \frac{1}{2} \times \left(\frac{l}{u_i} - \mu_2\right) \times \operatorname{erf}\left(\frac{\frac{l}{u_i} - \mu_2}{\sigma_2\sqrt{2}}\right) \\
&+ \left(-\frac{1}{2\mu_2}\right) \times \operatorname{erf}\left(\frac{-\mu_2}{\sigma_2\sqrt{2}}\right) \\
&- \frac{\sigma_2\sqrt{2} \times e^{-\left(\frac{l^2 - l_2}{\sigma_2/2}\right)^2}}{2\sqrt{\pi}} \frac{\partial_2\sqrt{2} \times e^{-\left(\frac{-\mu_2}{a_2/2}\right)^2}}{2\sqrt{\pi}} + \frac{l}{2u_i} \\
&- \frac{1}{2} \times e^{\mu_3 + \frac{\sigma_2^2}{2}} \times \left(\operatorname{erf}\left(\frac{-\ln\left(\frac{l}{u_i}\right) + \mu_3 + \sigma_3^2}{\sigma_3\sqrt{2}}\right) - 1\right) \\
&- \left(\frac{l}{2u_i}\right) \times \operatorname{erf}\left(\frac{\ln\left(\frac{l}{u_i}\right) - \mu_3}{\sigma_3\sqrt{2}}\right)
\end{aligned} \tag{1}
$$

2) A Vehicle Speed Estimation Method Based on Deep Learning: The probability-based analytical model indicates that the relationship between the number of CAs and vehicle speed is significant. Therefore, this study trains another neural network to estimate vehicle speed in accordance with the number of CAs. The input is the number of CAs and vehicle speed is adopted as the output of neural network.

B. Traffic Flow Estimation

The relationships between the number of NLUs and traffic flow were modelled by [1]. Therefore, this study supposes that one MS per operator is carried in each vehicle, and the NLU will be performed when the MS move into another location area. Therefore, the number of NLUs (q_i) is equal to traffic flow (Q_i) while a vehicle is passing through a LA.

C. Traffic Density Estimation

For traffic density estimation, the traffic density (k_i) can be estimated by Equation (2) according to the estimated vehicle speed (u_i) and the estimated traffic flow (q_i).

$$k_i = \frac{q_i}{u_i} \tag{2}$$

III. Simulation Analysis

The practical traffic information (i.e. traffic flow and vehicle speed) from [1] were adopted as simulation data in this study. For the generation of vehicle movement traces, the practical information contained road conditions (i.e., traffic flows) and vehicle movement behaviors (i.e., vehicle speeds). The vehicle movements were generated by VISSIM. This study assumed the following parameters: l_i=1.0 km, μ_i=1 call/h according to the statistical results. For MS communication behaviors, this study generated random numbers of call inter-arrival time with normal distribution for each MS. The simulation time is set to 24 hours. In simulation environment, this study supposes the length of a 3-lane freeway is 10 km with 11 handover points and 10 cells uniformly distributed on the whole road. The accuracies of vehicle speed estimation and traffic density estimation are described as $1 - \frac{|U_i - u_i|}{U_i}$ and $1 - \frac{|K_i - k_i|}{K_i}$. From TABLE I, the accuracies of estimated vehicle speed and estimated traffic density were 96.36% and 96.45%.

TABLE I
SIMULATION RESULT OF PROPOSED MODEL

Cell	U_i	K_i	u_i	k_i	$1 - \frac{\lvert U_i - u_i \rvert}{U_i}$	$1 - \frac{\lvert K_i - k_i \rvert}{K_i}$
1	81.27	64	80.06	64.65	96.13%	95.98%
2	80.68	64.37	80.83	63.98	96.71%	96.95%
3	80.29	64.68	79.86	64.79	96.66%	96.73%
4	80.06	64.84	80.51	64.21	95.46%	95.59%
5	79.92	64.98	79.76	64.84	96.73%	96.72%
6	79.8	65.08	78.88	65.59	96.74%	96.93%
7	79.69	65.19	79.99	64.66	96.42%	96.51%
8	79.58	65.28	80.27	64.43	96.50%	96.66%
9	79.57	65.31	80.32	64.29	95.35%	95.62%
10	79.48	65.38	79.73	65.07	96.85%	96.80%
		Average			96.36%	96.45%

IV. Conclusions

In this paper, a probability density function model was proposed to verify the relationships between the number of call arrivals and vehicle speed. A vehicle speed estimation method based on deep learning was proposed in accordance with the number of call arrivals. In experimental results, the proposed traffic information estimation methods have higher performance.

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