Compatibility Analysis of Travel Time Prediction on Freeway Using Loop Detector

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Abstract: Travel time is a representative index of travel systems. Several models and tools have been used to predict and estimate travel time, but few of them relate current speed and flow data with future travel time prediction. Differently, this paper combines the time template prediction and corridor travel time estimation together, based on the current point-level speed and volume data, to address the gap in the literature. Firstly, to predict the time stamp and speed of vehicles arriving at each loop detector, the METANET macroscopic traffic model is used for traffic state simulation. METANET takes real-time traffic measurements and simulates traffic state variables in a future time period. Then, segment-level travel time equals the travel time that is derived from the predicted speeds at the time of entering the section. From the piece-wise linear speed–based method (PLSB), the method assumes that speeds are changing linearly, and instantaneous travel time can be calculated. Based on the concept of “first in, first out (FIFO),” this departure time would be the starting time stamp of the next section. The speeds of vehicles are not fixed but instead dynamic, as they change from one moment to the next, so the time of sections would vary. When each section’s time boundaries are defined, the corridor-level travel time can be finally formed from adjacent sections by constructing imaginary vehicle trajectories. This paper tests, validates and links two practical models by using real-time loop detector data on Whitemud Drive in Edmonton, Canada.

Keywords— Speed, Volume, Travel Trajectory, Travel Time Estimation

1. INTRODUCTION

Travel time is considered a representative index of travel systems. Over time, several different models have been applied in travel time estimation. Earlier studies have mainly focused on algorithms based on historical speed and volume data, which were used in previous travel time characteristics estimation. For example, Wong and Sussman (1973) modeled algorithm parameters according to observed travel condition data to calculate travel time, while Chang and Mahmassani (1987) predicted travel time using a dynamic volume model based on changing driving patterns. However, the data sources of these models, such as probe vehicles, still have deficiencies. In contrast, the loop detector, a more recent development, serves as a comparatively efficient and accurate surveillance instrument that has improved the convenience and accuracy of data collection. The loop detector records information, such as speed, capacity, up and down volume, etc., in a rapid and efficient manner, and the captured data can reflect traffic conditions in real-time (Chen et al. 2007).

However, models based on historical data can hardly satisfy travel time estimation now, in the “Age of the Automobile,” as vehicle information and traffic conditions are much more dynamic than traditional driving patterns. Thus, predicting future patterns has become a more significant aspect in transportation research today. But, few studies in the literature focus on this aspect. Therefore, this study fuses the METANET model and the piece-wise linear speed–based (PLSB) method together to make a travel time prediction and estimation model.

The METANET-based dynamic traffic model, proposed for traffic flow estimation and control, can be seen as a macroscopic model. And because the model structure can be altered by adjusting parameter values, the model is flexible in how it corresponds to real-time traffic flow characteristics, and the accuracy can be demonstrated on a practical level.

A matrix of time stamps for speed or volume can be assigned; they are real-time and point-based ones, but travel time is a corridor-level index. Therefore, the PLSB method is appropriate (van Lint 2003), as it assumes that speeds vary linearly as a function of the distance between an upstream and downstream detector; in other words, speeds are changed linearly among travel sections. Hence, the study segment, which is from 122 Street at Whitemud Drive to 170 Street at Whitemud Drive, would be divided into several sections. Meanwhile, a random afternoon peak period (January 16, 2015) with dynamic speed is selected to compare predicted speed with the ground truth speed.

The objectives of this paper are the following:

a) To build a METANET-based dynamic model to predict the travel speed and volume per time interval under present traffic conditions, and improve its accuracy.

b) To apply the PLSB model to determine the assumed vehicle trajectory and calculate the travel time at the corridor level.

The remainder of this paper is divided into three parts. The first discusses speed and volume estimation, and the second considers how to link them together. And finally, a comparison of estimated travel time with the ground truth travel time is performed.

2. TRAVEL TIME ESTIMATION

2.1 The METANET-Based Dynamic Traffic Model

A METANET-based dynamic traffic model (Messmer and Papageorgiou 1990) was used to perform traffic state prediction. Below is a brief explanation of the prediction model. To apply the dynamic traffic model, the freeway corridor was divided into several segments (i =1, 2... N) of length L_i and lanes λ_i (as shown in Fig.1). The evolutions of traffic density $\rho_i(k)$ in vehicles per kilometer per lane (veh/km/ln) and traffic speed $v_i(k)$ in kilometers per hour (km/h) at each time index t (where, $t = kT$, T =the discrete time step, k = the time step presently in the calculation) were calculated by equations 1 and 2 (Spiliopoulou and Kopelias 2014):

[1] $$\rho_i(k+1) = \rho_i(k)+\frac{T}{L_i\lambda_i}(\lambda_{i-1}q_{i-1}(k)-\lambda_i q_i(k)+r_i(k)-s_i(k))$$

Where,
q = boundary flow between segments in vehicles per hour (veh/h);
R = on-ramp meter rates;
S = off-ramp flow.

[2] $$v_i(k+1) = v_i(k)+\frac{T}{\tau}\{V[\rho_i(k)]-v_i(k)\}+\frac{T}{L_i}v_i(k)[v_{i-1}(k)-v_i(k)]-\frac{\eta T[\rho_{i+1}(k)-\rho_i(k)]}{\tau L_i[\rho_i(k)+\kappa]}$$

$$V[\rho_i(k)] = v_{f,i}\exp\left[-\frac{1}{\alpha_i}\left(\frac{\rho_i(k)}{\rho_{cr,i}}\right)^{\alpha_i}\right]$$

Where,
τ = reaction term parameter in hours (h);
υ = anticipation parameter (km^2 per hour, km^2/h);
κ = positive constant (veh/km/ln)—these are global parameters that are calibrated from measured data.

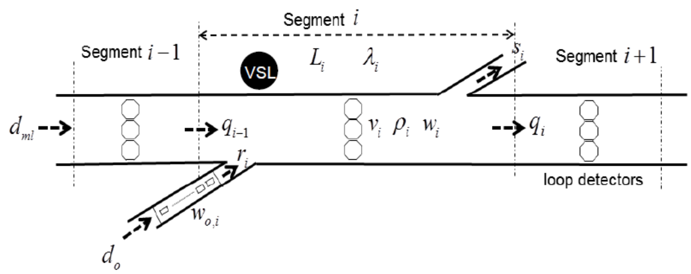

Figure 1: Segmentation of freeway links

2.2 The Piece-Wise Linear Speed–Based Trajectory Method

The piece-wise linear speed–based (PLSB) trajectory method can estimate travel time based on corridor level, assuming that the vehicle's traveling speed is dynamic. In the model, the time when a vehicle is passing over space [x_0, x_1] is defined as the time needed for a vehicle *i* to travel across particular section *k*. The speed *v*(x, t) depicts the steepness of its trajectory. In figure 2, the PLSB assumes that the steepness is a linear changing line. Thus, during calculation, compared to travel time estimation that assumes a constant traveling speed, the PLSB method can decrease the bias resulting from average speed calculation. In addition, in this paper, the estimation mainly focused on the position of *t* in the time axis. And in the adjacent section, the observed space (x_0 and x_1) and time (t^0_{ikp} and t^*_{ikp}) can be confirmed.

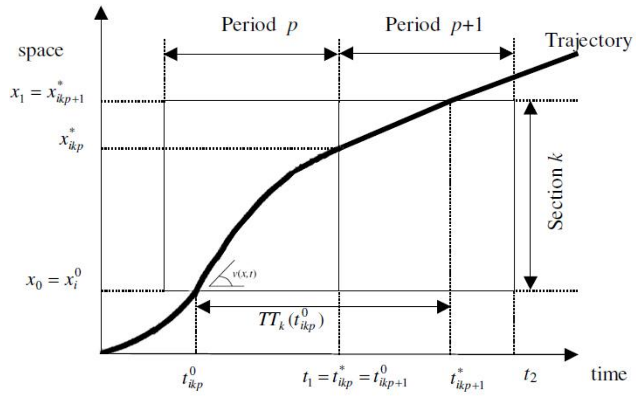

Figure 2: Trajectory through space-time cells (van Lint 2003)

As the number of lanes on the road will change in different sections, equation 3 is used to take into account the speed of each lane and calculate an average speed. This explains the average speed used in equations 4 and 5 (van Lint 2003).

[3] $v = \frac{\sum_{j=1}^{L}(q_i * v_i)}{\sum_{j=1}^{L} q_j}$

[4] $t = t^0_{ikp} + \frac{\ln\left[\frac{(x_i(t)-x^0_{ikp})}{\frac{V(d,p)}{A}}+1\right]}{A}$

[5] $A = \frac{V(d+1,p)-V(d,p)}{x_{d+1}-x_d}$

Where,
i = a vehicle;
p, P = measurement period and total number of measurement periods, respectively;
t_0, t_1 = start and end of measurement period p, respectively;
x_0, x_1= start and end location of section k, respectively;
L_k = length of section k;
$\{x_{0ikp}, t_{0ikp}\}$ = entry location and time of a vehicle in section k, period p;
$\{x^*_{ikp}, t^*_{ikp}\}$ = exit location and time of a vehicle in section k, period p;
$x_i(t)$ = trajectory of vehicle i as a function of time;
$v_i(t)$= speed of vehicle i as a function of time;
$V(k,p)$ = mean speed on section k during time period p.

The trajectory algorithm for a single vehicle trajectory can be schematically presented, as in figure 3 (van Lint 2003). It assumes that the time interval P is defined; in the space-time diagram, time stamps would be $n*P$ (0, P, 2*P, 3*P….i*P). When a vehicle enters region (k,p) at location (x^0,t^0), it exits at (x^*, t^*). Assuming that the whole travel time during this section range is p ($0 \leqslant p \leqslant$ i*P), if $p < P$, the vehicle will continue to the next distance section, and the travel time will be accumulated; this algorithm will be repeated until the sum of time $p > P$. In the next time interval, as the cycle repeats, the predicted values that fall within that interval are added up until the predicted travel time crosses into the next time period and so on. On the other hand, if in the first calculation $p > P$, the vehicle would leave this section at (x_1, p), and continue to travel on to the second section. From this method, vehicles' imagined trajectories can be built, and then the dynamic speed and tendency can be tracked. By using the travel time of each trajectory group in every section, the travel time of the whole corridor can be assembled. Finally, considering the travel time of vehicles with different trajectory types and their volume, the average travel time can be estimated.

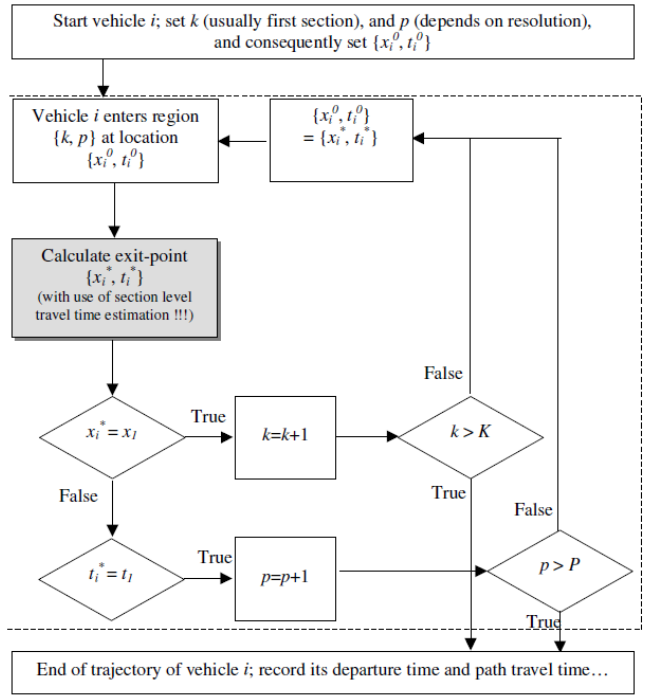

Figure 3: Trajectory algorithm for section-level travel time estimators (van Lint 2003)

2.3 Travel Time Example under Variable Traffic Conditions

The study site is from 122 Street to 170 Street at Whitemud Drive; this is a freeway with heavy traffic volume in the city of Edmonton, AB, Canada. The time section used for the study is from 4:29 pm to 5:30 pm on a Friday, which is during peak hours. The traffic condition is illustrated in the following figure:

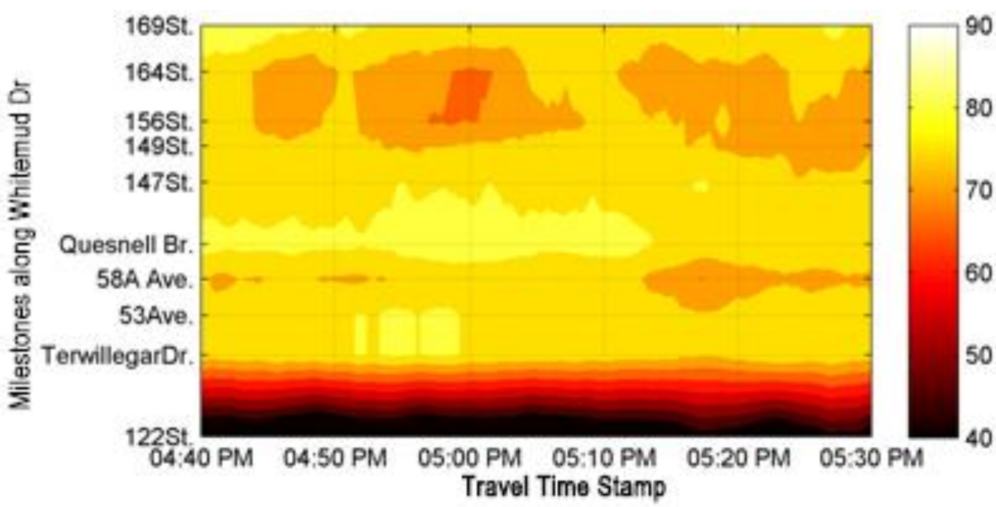

Figure 4: Trajectory method for section-level travel time estimators

For the reason that 122 Street is a major road that links south Edmonton with downtown, the graph depicts congestion during the whole time, which is the reason for the speed being less than 60 km/h. And on the road from 156 Street to 169 Street, the speed is lower than 70 km/h after 5:00 pm.

According to the PLSB method, the corridor should be divided into sections. After considering the loop detector position and operation situation, the resulting division is shown as follows in Figure 5:

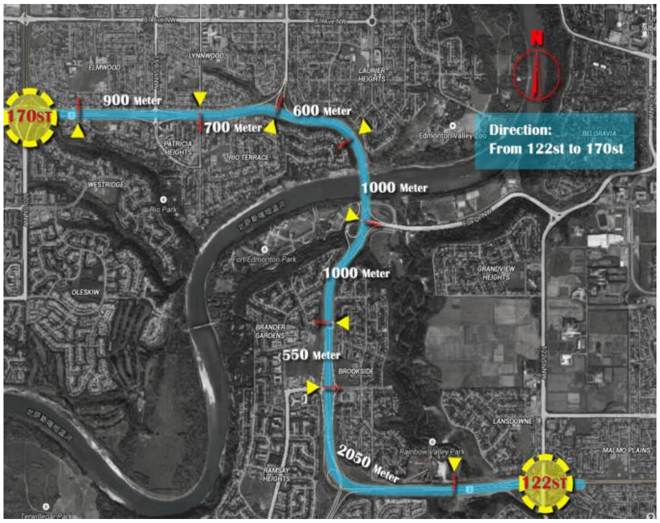

Figure 5: Section on Whitemud Drive

Table 1: Distance of sections

Section (No.)	Intersection (At Whitemud Drive)	Distance (Meters)
1	122 St - 53 Ave	2050
2	53 Ave - 58 Ave	550
3	58 Ave - Fox Dr	1000
4	Fox Dr - 142a St	1000
5	142a St - 149 St	600
6	149 St - 156 St	700
7	156 St - 170 St	900

In this paper, in order to make the simulated result similar to actual loop detector data after optimization at the greatest extent, fundamental diagram-related parameters $\left[v_f, \rho_{cr}, \alpha\right]$ of the METANET model were calibrated to be [80, 35, 2.8] based on field traffic data. Similarly, with the given demand inputs for mainline and on-ramps, the global parameters [τ, υ, κ] in equation 2 were optimized by Sequential Quadratic Programming at 0.02, 28.8, and 10, respectively. In the graphs in figure 6, it is shown that with when the parameters are defined, simulated speeds are almost the same as in real time, except for section 1 with speeds around 80 km/h, higher than real-time speeds, which are around 65 km/h. This is mainly due to the reason that in this section, the predicted result is calculated from the data of 122 Street at Whitemud Drive, where there is recurring congestion. Thus, the speed is lower than the freeway speed of Whitemud Drive.

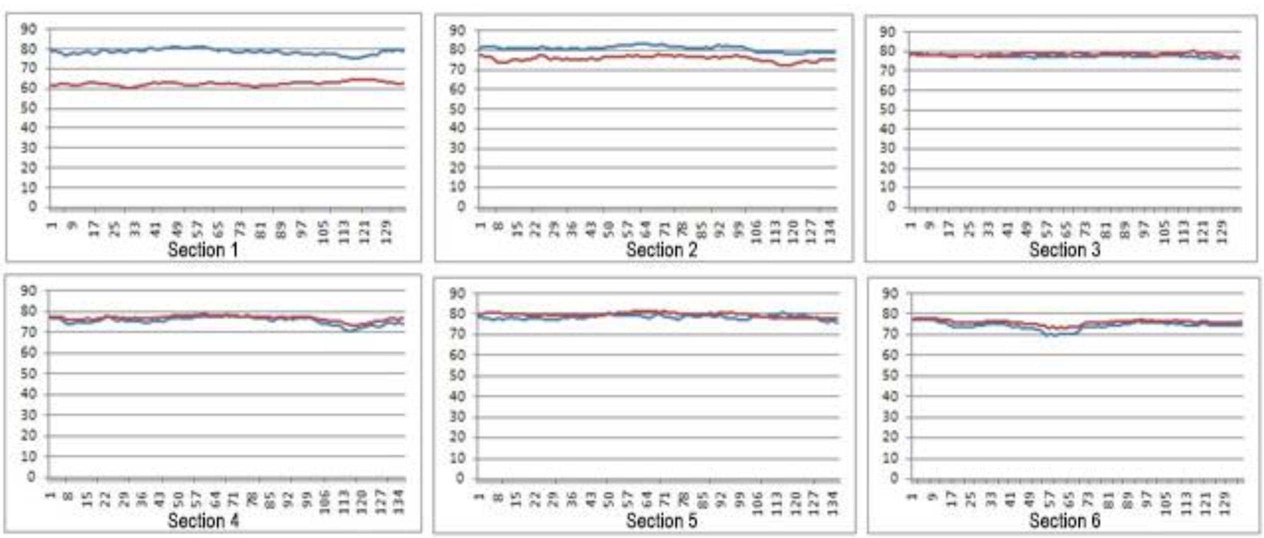

Figure 6: Speed comparison between estimated data and actual data

In order to make a comparison, travel time and trajectories were calculated based on the METANET model estimated data and actual loop detector data individually.

Table 2: Result of METANET model estimated data

Type	Trajectory Number of vehicles	Travel Time (sec)	
1	11	0	367.0
2	1	0	370.582
3	4	0	389.1
4	1	0	375.0
5	44	0	374.0
6	2	0	382.7
7	6	0	376.3
8	51	0	379.0
9	3	0	386.1
Average Time		0	376.4

Table 3: Result of actual loop detector data

Type	Trajectory Number of vehicles	Travel Time (sec)	
1	5	0	418.0
2	3	0	418.0
3	1	0	420.0
4	2	0	417.3
	…		
13	2	0	423.7
14	4	0	424.0
15	6	0	423.3
16	4	0	422.1
Average Time		0	385.1

In table 3, there are 16 trajectory types for the actual loop detector data, and the number of vehicles varies from one to six. Whereas in table 2, for the METANET model, there are only nine trajectory types for the estimated data. It is apparent that trajectories of the actual data were more random. This is due to the reason that, after being modeled, the noise of the actual data would be decreased, and then the vehicles would be grouped according to trajectory type. Types 1, 5 and 8 in table 2 have more vehicles than the other trajectory types.

As shown in tables 2 and 3, the estimated travel time calculated from actual detector data was 385.1 seconds, compared to 376.4 seconds, as computed from estimated data under the METANET model, but the difference of 8.7 seconds was only 2.3% of 385.1 seconds, so the deviation was not significant.

For ground truth data in table 4, which were produced from camera records after data filtering, there were 35 vehicles that could be assigned as ground truth vehicles. The travel time varied from 354 seconds to 463 seconds. It showed that when reaching the peak traffic hour (5:00 pm–6:00 pm), the travel time of targeted vehicles would be even longer, nearly 100 seconds. The average travel time of the ground truth data was 391.3 seconds, about 14.9 seconds and 6.2 seconds more (about 3.8% and 1.6% of 391.3 seconds, respectively) than previous estimated travel time data, according to estimated data and actual data respectively.

Table 4: Results of ground truth

No.	Time template (PM) 122	170	Travel time (sec)
1	3:04:35	3:10:49	374
2	3:05:37	3:11:46	369
3	3:07:33	3:13:27	354
4	3:07:37	3:13:37	360
5	3:09:45	3:16:18	393
	…		
31	4:24:55	4:31:38	403
32	4:28:25	4:35:48	443
33	4:47:54	4:55:28	454
34	4:49:28	4:56:48	440
35	4:57:19	5:06:02	463
Average Time			391.3

Figure 7 shows that for every 10 minutes passed, the targeted vehicle number will decrease during data collection. This is mainly caused by the decrease of daylight in winter time.

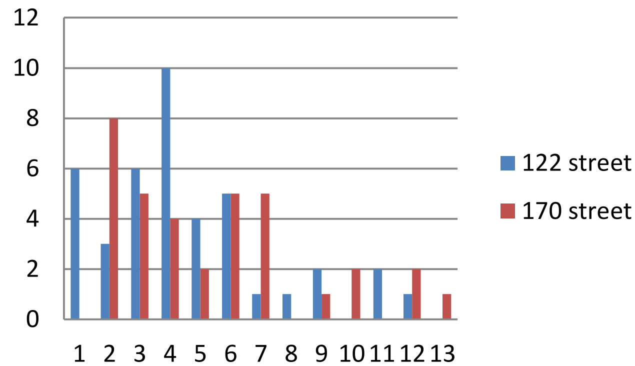

Figure 7: Number of vehicles every 10 minutes

Figure 8 depicts the travel time for vehicles traveling from 122 Street to 170 Street along Whitemud Drive every 10 minutes, demonstrating an overall increasing trend. The reason for this trend is that, on Friday, starting from 4 pm, there would be many vehicles returning from towns and industries outside of Edmonton. Especially around 6 pm, heavy congestion may happen along this corridor.

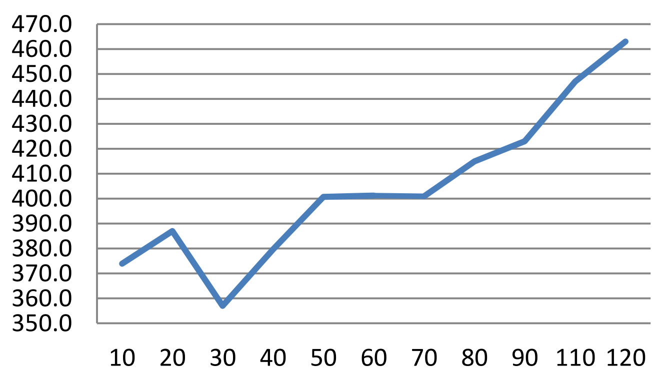

Figure 8: Average time of vehicles every 10 minutes

3. CONCLUSION

In this study, the estimated result of 385.1 seconds was similar to the ground truth result of 391.3 seconds. This demonstrates that with this improved PLSB model, travel time based on corridor level can be calculated relatively accurately with two conditions. One is the assumption of a convex combination of dynamic speeds rather than a constant speed, and the second is imagined vehicles' trajectories, which can reduce bias from dividing travel vehicles into various groups and transferring section-level–based travel time into corridor-level–based ones. Then, even though there have different travel time estimation models based on loop detector data, for example, the PCSB trajectory method (Coifman 2002) and the (AKF) adaptive Kalman filter method (van Lint 2003), the PLSB still shows its advantages in accuracy for the previous two conditions.

In practice, some loop detector facilities along the road do not work perfectly all the time, or we may need current data to make a future forecast of travel conditions. The METANET model can help to achieve this. In the paper, the result only differs 14.9 seconds from the ground truth. Compared to 391.3 seconds, it is still an acceptable deviation.

Even though the combination of the METANET and PLSB models can provide a relatively precise estimation of corridor travel time, there are still some factors that influence accuracy. In the METANET model, when high traffic density or congestion occurs on the road, the bias from actual speed and volume will increase. In addition, in the process of filtering ground truth data, the randomness of the vehicle, the limitation of light, and the delay of camera information reflection would lower the veracity of the ground truth data.

In future work, this paper will mainly work on improving the testing environment, data filtering and model simulation level, as well as other aspects. In addition, future work will involve more data collection by using probe vehicles to collect ground truth data, adjusting the study time segment, and so on. By performing these adjustments, a more efficient travel time prediction model can be built in later research.

4. ACKNOWLEDGEMENTS

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