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Optimal Averaging Time for Predicting Traffic Velocity using Floating Car Data Technique for Advanced Traveler Information System

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Abstract

Many metropolitan cities are facing the problem of traffic congestion in large scale and high frequency. The congestion can be lessening by employing Intelligent Transportation Systems (ITS) including Advanced Traveler Information Systems (ATIS). ITS systems have been demonstrated and implemented in few advanced countries. For an example, the technology of Electronic Toll Collection (ETC) in Japan has completely eliminated the traffic congestion ahead of toll gates and has reduced CO2 emission by 130000 ton-per-year. Recently, an ATIS system so called Floating Car Data (FCD) technique has received many attentions due to its cost-effectiveness and wide coverage in comparison to traditional systems in providing real-time traffic information. The success of the technique is made possible with the existing and vast coverage of the wireless network and information technology. In regard to FCD technique, although many publications have discussed various issues, none has elaborated the traffic data discrepancy between that provided by the FCD technique and the actual traffic data. This paper discusses the issue and demonstrates that there is an optimum averaging time interval in the FCD technique such that the data recorded by a probe vehicle can reasonably predict the traffic flow. The analysis is based on experimental data recorded by Sugiyama et al. (2008) where 22 vehicles were deployed to establish a platoon of vehicles moving in a circular road having 230 m perimeter length. Various averaging time intervals are studied, and one that provides the best estimate of the traffic flow is selected as the optimum averaging time interval.

Keywords: Intelligent Transportation Systems (ITS); Advanced Traveler Information Systems (ATIS); Floating Car Data; Optimal Averaging Time Interval; Ergodicity

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1. Introduction

Traffic congestion in Asian megacities has become extremely worse. Recently, the Indonesia Ministry of Economic Coordination asserted that the inhabitants of Jakarta and greater spend about 60% of their travel time in the traffic jam. Therefore, reducing the level of congestion is an issue of great interest.

To solve the congestion problem, building an efficient and high capacity mass transportation system is clearly necessary (Morichi, 2005). In addition, implementing Intelligent Transportation System (ITS) has also been demonstrated to be effective (Nelson et al., 2001; Toshitaka, 2007). In Japan, Electronic Toll Collection (ETC) has completely eliminated congestion ahead of the toll gate and reduces CO2 emissions by 130000 ton per year (Toshitaka, 2007).

ITS is essentially a combination of the transportation system and the information technology system. The two systems interact such that the transportation system can be managed more efficiently. This interaction is possible by means of a set of enabling technologies including data acquisition, data processing, data communication, information distribution, and information utilization (Chen and Miles, 1999). ETC is an excellent example of ITS applications. Another ITS application is Floating Car Data (FCD), which is designed to provide a real-time traffic data by means of probe vehicles.

Many publications have discussed various aspects of FCD technique. Sanwal and Walrand (1995) was one of the earliest publications prior the smartphones era. Cathey and Dailey (2001) discussed the use of transit vehicles, proposed a Kalman filter to estimate the vehicle position and velocity, compared the estimated velocity to those measured by a speed-trap, and developed a graphical application to display the data in real-time. Dai et al. (2003) studied the use of FCD using a microsimulation model, and evaluated the technique performance in terms of accuracy, reliability, timeliness, and coverage. The accuracy of link speeds was defined as:

\[
C_v = \text{Prob}\left(\frac{|\epsilon_v|}{\epsilon_i} \right)
\]  

Where \(\epsilon_v\) is the relative error in link speeds between traffic and probe vehicles, and \(\epsilon_i\) a threshold level (5%, 10%, 15%, etc.). Finally, they concluded that the number of probe vehicles was critical for coverage and accuracy, and recommended a penetration rate of 3% for freeways and 5% for surface roads, where the penetration rate was defined as the number of probe vehicles during an averaging time interval \(t_a\) on a traffic link having a flow rate \(Q\).

In addition, Fabritiis et al. (2008) presented a large scale implementation of a traffic management system, so called OCTOTElematics FCD system. At that time, the system received traffic data from 600000 private vehicles. The paper also proposed the artificial neural network and pattern matching algorithms for short-term prediction of travel speed. They evaluated algorithm using the traffic on the Roma Ring Road, which has a length of 68.2 km with 2.4% penetration rate, 33 entries/exists, and 15000 floating cars in workdays. Uno et al. (2009) proposed a method to use transit buses enriched with GPS sensor as probe vehicles. The bus was then used to measure the travel time data, and a procedure was proposed to estimate the associated road travel time. Liu et al. (2009) evaluated the reliability of using taxi dispatch system for real-time traffic information. They found that although among commercial vehicle operations, taxi was the most appropriate for the purpose, but it suffered on a number of issues. Their findings were: Taxi provided good traffic data on high demand links, but the dispatch system could not be a single source of real-time; data from vacant taxis needed careful consideration; GPS location errors had little impact on traffic monitoring, however, the system provided good data for a long road segment. Herrera et al. (2010) was the first field experiment that capable to maintain 2–5% penetration rate involving 100 vehicles to cover a 10–16 km long freeway. Campolo et al. (2012) developed an integrated smartphone-based platform to acquire, transfer, process, and display traffic and vehicle related data.

Despite of many existing publications and conviction that the accuracy given by the technique depends on the penetration rate, see Equation (1), and the averaging time interval \(t_a\), none of those publication has quantified and describe how do the averaging time interval affect the accuracy of the FCD technique. This article will discuss this critical issue based on well-controlled field experiment where the penetration rate was maintained at a constant rate during the experiment.
2. Floating Car Data System Description

The present infrastructure for the floating car data system is depicted in Fig. 1. The system has three main components, namely, a probe client, a web server, and a web client.

Currently, the probe client utilizes a smartphone, which is a hand-held device that integrates the functionality of a mobile phone with other features but mainly with geo-location functionality. The probe client is attached to a probe vehicle and is used to measure the probe vehicle position, velocity, and heading. Finally, those data and related timestamps will be transmitted to a server via a wireless network.

In the current development, the probe client is an Android application installed in a mobile phone, and the phone will be attached to a probe vehicle. The Android application is designed according to the software architecture depicted in Fig. 2. The application uses Android API and its underlying system to access the built-in GPS receiver unit. The GPS unit provides data related to the phone position, velocity, bearing, accuracy and timestamps. Those data are then preprocessed and finally are transmitted to the web server via the 3G network.

Meanwhile, the software architecture of the server side applications for FCD traffic monitoring is shown in Fig. 3. The server side consists of web server, client, 3rd party web services, and probe subsystems. The web server is the core system that collect, process, store, and provide traffic information. The system has two features: web service and web application. The web service communicates with probe clients to receive updates of the traffic data. The other feature, web application, is accessible from client web browser to retrieve traffic information. The client web browser is the only component accessible by end users. The web application will instruct a client web browser to load map provided by Google Maps API, and will overly traffic information on the map.
The web service and web application is a single system build on top of CodeIgniter framework, which uses PHP programming language. The use of CodeIgniter framework is preferred since it offers numerous technical advantages and organizational advantages, such as faster development and cleaner application structure, in comparison to developing native PHP application (Vuksanovic and Sudarevic, 2011). PHP is installed as a module on Apache web server and also integrated with MySQL database server.
3. Research Method

This work is performed based on the data recorded in the experiment performed by Sugiyama et al. (2008). The experiment involved a platoon of 22 vehicles moving along a circular road in a homogeneous lane condition on flat ground. The road length was 230 m. Each driver was requested to maintain a safe distance to its leading vehicle or if possible, to cruise at a velocity of 30 km/h. Basically, Sugiyama et al. (2008) intended to experimentally verify occurrence of the phantom traffic jam.

In the experiment, a 360-degree video camera was set at the center of the circular road and was used to record the vehicle positions at a rate of one-third of a second. Therefore, the experiment resulted on data sampled at regular time instances. However, for the purpose of the current study, the required data are those at specified instant of spaces. The Sugiyama et al. (2008)'s data are reproduced in Fig. 4 for self-reliance of this article.

![Fig. 4. The space-time diagram of the 22 vehicles recorded in the Sugiyama et al. (2008)'s experiment.](image)

As stated previously, for the current purpose, the 22-vehicle velocities should be able to be evaluated at a specified location. The traffic velocity in the practical application is usually monitored by means of loop detectors implanted at the location beneath the road surface. To obtain the data for the current purpose, the original data are manipulated as the following.

Firstly, the data are unwrapped to obtain a continuous vehicle trajectory in space. The unwrapped data and the associated velocity data are shown in Fig. 5. Subsequently, the unwrapped data are smoothed out using the 9-point moving averaging (MA) method to eliminate negative vehicle velocity. The 9-point method is selected after evaluating various number of smoothing points including: 3-point, 5-point, …, 21-points. The decision was made to use the 9-point method because the method was able to eliminate the negative vehicle velocity and minimally adjust the original data.

Secondly, the trajectory of each vehicle is fitted with a cubic spline function \( s(t) \) with smoothing. The function essentially minimizes the measurement error and the function smoothness, or mathematically is written as (de Boor, 2001):

\[
p \sum_i w_i | x_i - s(t_i) | 2 + (1-p) \int_a^b | D^m s(t) |^2 dt.
\]

In the equation, \( p \) is a smoothing parameter, \( x_i \) is the vehicle position data at the measurement index \( i \), and \( w \) is a weighting factor.

Thirdly, after establishing the cubic spline function \( s(t) \) for each vehicle, we can now easily differentiate the function to obtain the vehicle velocity at any location. As a result, in Fig. 6, we plot the platoon average velocity and its variation along the observed road segment. The line denoted by 'mean' represents the average velocity of the
platoon. The upper limit and lower limit denote the velocity variation and are measured with respect to the standard deviation of the vehicle velocities. Afterward, we denote the velocity as $v_{\mu}^P$, which is the average velocity at a measurement point $X$. Therefore, in relation to Sugiyama et al. (2008)'s experiment, the data represent an average of 22 vehicles. Those vehicles required about 33 s to traverse a measurement point.

Traditional measurement system based on loop detectors clearly provides the traffic velocity $v_{\mu}^P$ data. However, in the perspective of the floating car data technique, only historical data of a single probe vehicle are available at the point of interest. If we denote the traffic velocity estimated by the floating car data technique as $v_{\mu}^T$, we expect the estimated velocity by the technique to reasonably represent the actual traffic velocity $v_{\mu}^P$.

We should note that $v_{\mu}^T$ depends on the averaging time interval $t_a$. A short $t_a$ will naturally lead to a highly fluctuating estimated $v_{\mu}^T$. On the contrary, a long $t_a$ will produce overly firm estimated velocity. In this work, we evaluate $v_{\mu}^T$ for various $t_a$ and describe how the variable affects the estimated velocity.

4. Basic Theory

We support the current study with two assumptions. The first is that the average speed of a stream of vehicles on a road is assumed to be a stationary random process. The stationary assumption implies that its statistical properties—for examples, its mean and standard deviation values—will not change across the time. Mathematically speaking, for a random process $v(x,t)$, then the mean $v_{\mu}^T$ can be estimated by

$$v_{\mu}^T = \frac{1}{2T} \int_{-T}^{T} v(x,t) dt .$$

The second assumption is: the random process is ergodic, which implies that the above statistical properties can also be obtained by the ensemble average of the process, or:

$$v_{\mu}^T = \frac{1}{2X} \int_{-X}^{X} v(x,t) dx .$$

In relation with the traffic engineering, the average speed of a traffic flow that obtained by the loop detector technique is clearly a result of Equation (4) where the loop detector is implanted across the traffic lanes. Meanwhile, the more modern technique of FCD can easily be used to reduce the speed by Equation (3).

5. Results and Analysis

Firstly, we analyze the platoon dynamic at many positions across the road segment. Those positions are located in a pre-determined range of [0.36 km, 1.60 km] with a regular spacing of 2.4 m. This region is marked as monitored segment in Fig. 5. The platoon dynamics is represented with its average velocity ($v_{\mu}^P$) and standard deviation ($v_{\sigma}^P$) at these positions, and is graphically shown in Fig. 7. In the figure, the upper and lower limits denote $v_{\mu}^P \pm v_{\sigma}^P$, respectively.
Therefore, the mean velocity in the figure can be regarded as the traffic velocity at the observation point and is usually obtained via loop detector implanted on the road. In this case, the traffic velocity is an average of 22 vehicles, which require about 33 s to cross a measurement point.

We need to note that in the case in Fig. 7, the phantom traffic jams that occur for a short duration lead to high variation in the individual vehicle velocity. However, prior the jam, the vehicle velocity is relatively uniform across those 22 vehicles. When this fact is related to the traffic measurement using a probe vehicle, we naturally expect that the vehicle will provide a poor prediction when the velocity variation is high and a better prediction when the velocity variation is relatively uniform.

A comparison of the probe vehicle velocity and the platoon average velocity is shown in Fig. 8. The probe vehicle is randomly selected, and the averaging time is varied as 1 s, 15 s, and 30 s. However, we limit our analysis prior the onset of the traffic jam.
Fig. 7. Comparison of the platoon mean velocity ($v_{av}^P$) and the probe vehicle velocities at averaging time interval ($t_a$): 1 s, 15 s, and 30 s.

Fig. 8. The optimum averaging time for various probe vehicles. Three vehicles have optimum averaging time interval of 5 s and 8 s; the median is 7 s, and the mean is 6.8 s.

The figure indicates that prior occurrence of the phantom jam, the discrepancy between the probe vehicle velocity and the platoon average velocity is rather consistent. For $t_a = 1$ s, the probe vehicle overestimates the velocity peaks and underestimate the velocity valleys, consistently. However, for $t_a = 30$ s, the result is on contrary. Figure 8 clearly indicates that there is an optimum averaging time interval $t_a^*$ that minimizes the relative error (see Equation (5)) of data between the two methods of measurements, and for the present case, we are certain that $1 < t_a^* < 30$ s.

\[
\text{Relative Error} = \frac{\|v_{av}^{X} - v_{av}^{P}\|}{\|v_{av}^{X}\|} \times 100\% \tag{5}
\]

Table 1 presents the analysis for various time averaging interval $t_a$. A summary is given in Fig. 9, which shows that the mode of the averaging time interval is 7 s, and the average is about 6.8 s. At this averaging time interval, the estimation error of the FCD is about 4%-6%. Figure 10 compares the best estimates of the velocities by the both measurement methods.
Table 1. The relative error between the probe vehicle velocity and the platoon average velocity for various averaging time interval $t_a$

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Fig. 9. A comparison of the platoon mean velocity ($\bar{v}_P$) and the best estimate of the probe vehicle velocity ($\hat{v}_P$) at the averaging time interval $t_a = 7$ s.

6. Conclusion

Recently, an advanced traveler information system, so-called floating car data technique, has received much attention due to proliferation of smartphones. This type of phones is enriched with a module that capable to receive signal for navigation from a satellite navigation system such as GPS and GLONASS. By exploiting this feature, we can now provide traffic information in real time at a very low cost. For this purpose, the smartphone is usually attached in a probe vehicle and moving along with the vehicle to record the traffic information. Finally, the phone should preprocess and transmit the information to a central processing server where the information will be presented to the traveler. As result, many factors can potentially affect the accuracy of the traffic information...
gathered by the method, for instances, the accuracy of the signal receiver, the velocity of the probe vehicle, and the averaging time interval. This article discusses and quantifies how the averaging time interval affects the accuracy of the result by the FCD technique. Using data obtained from a well-controlled vehicle stream with a constant penetration rate of 4.6%, we demonstrate that there is an optimum averaging time interval that provides highest accuracy of the traffic velocity. For the current traffic condition, the optimum value is about 7 s. The current recommendation still needs further assessment based on data obtained on various actual traffic conditions.

References


