Proceeding Paper

Traffic Stream Characteristics Estimation Using in Pavement Sensor Network †

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Abstract: Numbers of vehicles has increased tremendously on roads. Also, the number of roads that are constantly experiencing traffic jams during morning and evening peak hours has increased significantly, which calls for a better understanding of traffic stream characteristic and car-following models. Traffic stream macroscopic parameters (speed, flow and density) could be estimated through a number of traffic-flow theory models. In order to collect accurate data regarding fundamental of traffic stream parameters, a traffic monitoring system is needed to present the data from different roads. In this study, a real time traffic monitoring system is introduced for traffic macroscopic parameters estimation. The sensor network has been constructed using a set of linear fiber optic sensors. In order to validate the system for this study, the system was installed at MnROAD facility, Minnesota. Fiber optic sensor detects the propagated strains in highway pavement due to the vehicle movements through the changes of the laser beam characteristics. Traffic flow can be estimated by tracking the peak of each axle passed over the sensor or within the sensitivity area, Time Mean Speed (TMS) and Space Mean Speed (SMS) space mean speed can be estimated by the different time a vehicle arrived at the sensors. The density can be determined either by using fundamental traffic flow theory model or estimation the time that vehicles occupy the sensor layout. A real traffic was used to validate the sensor layout. The results show the capability of the system to estimate traffic stream characteristics successfully.

Keywords: traffic stream; macroscopic parameters; ITS; in-pavement sensors; traffic data

1. Introduction

The number of vehicles has increased tremendously on roads due to rapid economic growth and urbanization as traffic volume increases on highway networks, contributing to traffic congestion, vehicle accidents, traffic safety, energy consumption, economic impact due to fuel and time waste, and green gas emission [1–3]. To better understand and overcome the traffic volume increment problems, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) interactions must necessarily be studied [4]. Traffic flow theory plays a critical role in understanding V2V interactions through a set of macroscopic parameters, including flow (q, vph), density (k, vpkm), and speed (S, kmph). These parameters could be estimated by a process called Traffic State Estimation (TSE), where an accurate estimation of macroscopic parameters (q, k, and s) plays a central role in the success of the developed traffic management system to mitigate traffic congestion problems [1]. Furthermore, TSE is vital for traffic planning (infrastructure management, maintenance) and traffic management (traffic control, ramp metering) [5].

Currently, the collected traffic data type can be sorted into two categories based on the measurement method: stationary data collected through fixed detectors, including loop detectors, inductive loops, closed-circuit television cameras (CCTV), fiber optic sensors [5–8]; mobile data, such as on-vehicle GPS probe, OBD2, mounted video cameras,

mobile phone, connected vehicle [5,9]. Despite expanding the use of mobile-collected data recently, it has problems with sampling and shows the potential for biases [5]. However, stationary collected data through fixed sensors represents every vehicle at their installed locations.

Fiber optic sensors have become widely accepted in traffic management and operation [10,11]. Fiber Bragg Grating (FBG) sensors are preferred among fiber optic sensors due to the distinctive characteristics that give them superiority over counterparts from other fixed sensors, including good linearity in response, accurate output, high resolution, small size, and low cost [12]. However, FBG sensors must be packaged since they are made of fiberglass. Currently, Glass Fiber Reinforced Polymers (GFRP) is used in several fields, such as oil and gas, the pipe industry, structural elements, and aerospace [13], which makes it promising to be used as FBG sensor package material. Thus, this study introduces a stationary system for traffic stream parameter estimation based on GFRP-FBG sensor layout.

2. Sensor Fundamental

FBG sensor detects propagated strains (ε) in highway pavement due to vehicle movements through the changes in the laser beam characteristics, as shown in Equation (1) [14]:

$$\varepsilon = \frac{1}{(1 - Op)} \left(\frac{\Delta\gamma_l}{\gamma_l} - \frac{\Delta\gamma_T}{\gamma_T}\right) \tag{1}$$

where, Op is the optical elasticity parameter, γ_l is the Bragg wavelength due to mechanical load and temperature, and γ_T is the Bragg wavelength from a compensation temperature sensor.

Figure 1. shows the developed GFRP-FBG sensor by Zhou et al. [15], which will be used in this study for traffic stream characteristics estimation. Figure 1a shows the longitudinal component of the sensor, which is designed to detect the propagated strain in the x-y coordination. Figure 1b illustrates the vertical component of the sensor to monitor vertical strain.
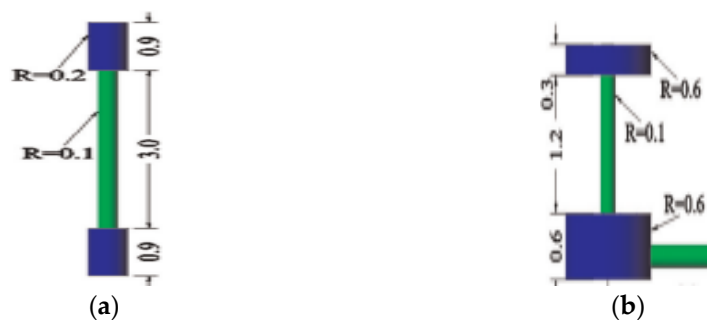

(a)   (b)

Figure 1. GFRP-FBG sensor: (**a**) Longitudinal sensor; (**b**) Vertical component sensor. All units in (in.).

3. Methodology

To construct a traffic stream characteristics system, a minimum of two GFRP-FBG sensors must be installed along the road sequentially with a distance of (L) under the proposed vehicle tire track to increase the accuracy of the sensor measurements, with one FBG sensor to compensate for the temperature cross-sensitivity. Figure 2 shows the proposed sensor layout to estimate traffic macroscopic parameters, which consists of three GFRP-FBG sensors: A horizontal sensor (H-S), a vertical sensor(V-S) to track vehicle movement, and a horizontal temperature compensation sensor (H-TS). In this study, the distance L will be 4.87 m, which falls between the optimized distance interval from 2.13

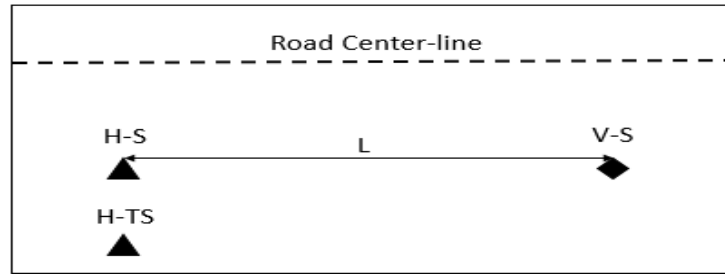m and 6.1 m to maximize the measurement accuracy for macroscopic parameters estimation.

Figure 2. Proposed sensor layout.

Estimating the traveled time for each passing vehicle between the two stationary sensors plays a vital role in deriving all macroscopic parameters (q, k, and s). Figure 3 illustrates the responses from the H-S sensor (positive measurement due to tension in the pavement along the road) and the V-S sensor (negative measurement due to compression at the location of the vertical sensor) for two consecutive vehicles (5 axle leading vehicle, and 2 axle following vehicle).
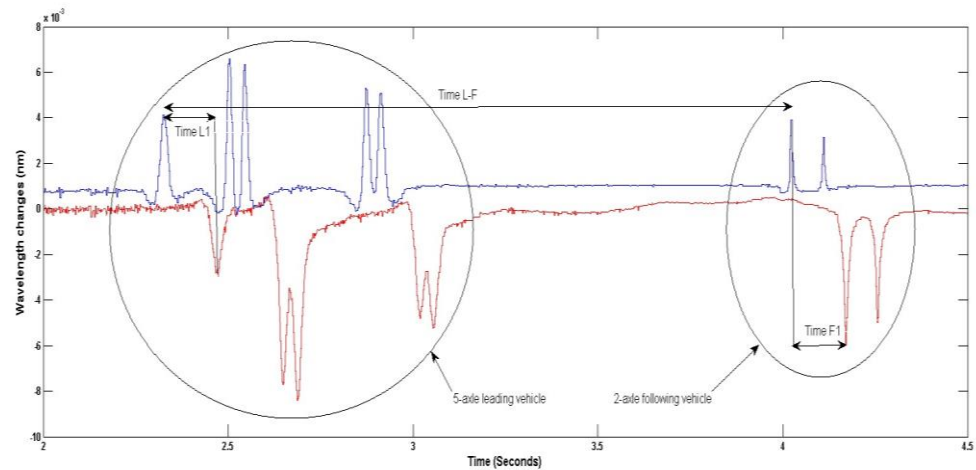

Figure 3. Sensor's response.

As noted in Figure 3, the sensor response will be more likely to have a peak shape due to the compact sensor's size and higher vehicle speed, where each peak indicates the passing of one axle. Thus, the peaks will be tracked and counted accordingly for traffic flow (q) estimation, as stated in Equation (2). The recorded time (Time L1, and Time F1) indicates how long each vehicle travels over the known distance of (L) between the horizontal and the vertical sensors. Then, Time Mean Speed (TMS) and Space Mean Speed (SMS) can be calculated using Equations (3) and (4), respectively.

$$q \ = \frac{N}{T} \tag{2}$$

$$TMS \ = \frac{\sum_{i=1}^{N} L/t_i}{N} \tag{3}$$

$$SMS \ = \frac{N.L}{\sum_{i=1}^{N} t_i} \tag{4}$$

where, N is the total number of vehicles in a period of time (T), and t_i is the traveled time for a vehicle (i).

Therefore, density (k) can be calculated using the fundamental flow-density relationship, as follows:

$$k = \frac{q}{SMS} \tag{5}$$

4. Results and Discussion

To validate the system for traffic stream macroscopic estimation, the sensor layout was installed at the Cold Weather Road Research Facility in Minnesota (MnRoad) in Mn, USA. MnROAD consists of 50 test sections distributed on two roadways: A low-volume loop operated by 5 axle semi-truck, and a section of (I-94) that contains two lanes operated by live traffic. The proposed sensor layout (Figure 2) was installed inside cell 17, part of I-94 at MnROAD, as shown in Figure 4.
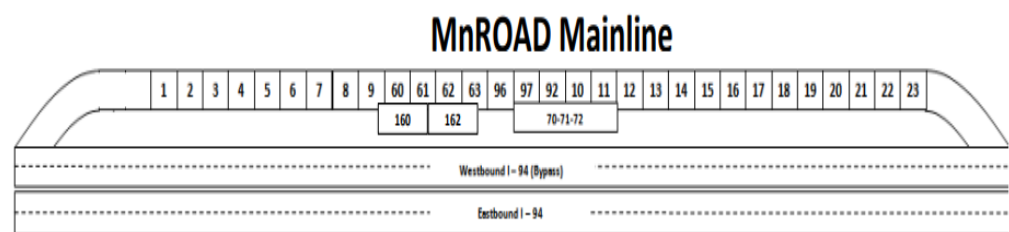

Figure 4. MnROAD test section.

After the installation, the sensors were connected to a high-resolution integrator and personal computer to collect data. Figure 5 shows the response of both sensors (Vertical and horizontal) when subjected to real traffic for 140 s to validate the system. From Figure 5, a total of 11 vehicles were recorded and tracked by the system. Thus, the flow (q) could be estimated, as equal to 283 vph.
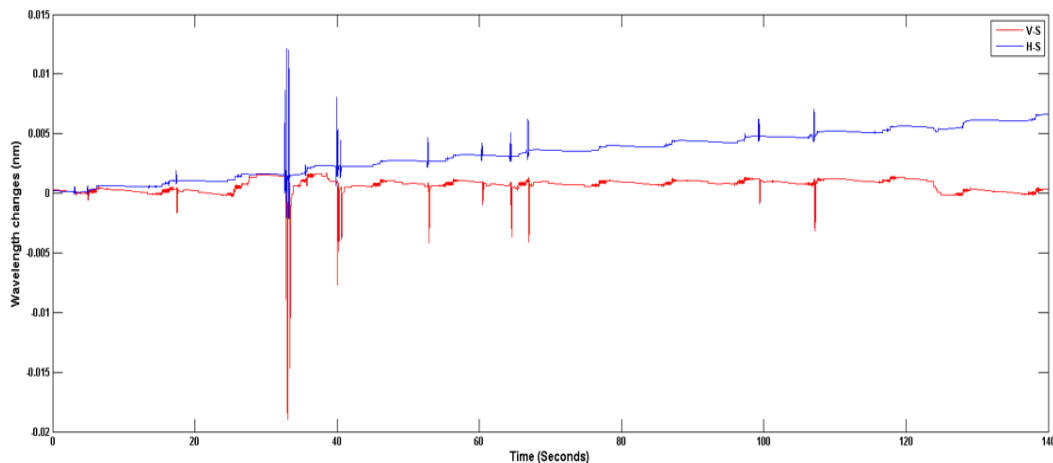

Figure 5. Sensors' response for 140 s.

Table 1 shows the estimated spot speed for the eleven vehicles recorded during 140 s, since the distance between sensors in the layout is defined (4.88 m). The system records the time the vehicle enters the sensor layout (Tin) and when the rear wheel exits the layout (Tout) to calculate the travel time for each vehicle, as shown in Table 1. Then TMS, SMS, and K can be calculated using Equations (2)–(4), respectively. Therefore, TMS equals to 110.00 km\h, SMS equals 108.74 km\h, and K equals to 2.6 v/km.

Table 1. Estimated spot speed.

Vehicle	T_{in}	T_{out}	Travel Time (s)	Spot Speed (km/h)
1	4.923	5.069	0.146	120.25
2	17.44	17.58	0.14	125.40
3	33.23	33.4	0.17	103.27
4	35.61	35.78	0.17	103.27
5	40.52	40.68	0.16	109.73
6	52.82	53	0.18	97.54
7	60.41	60.58	0.17	103.27
8	64.44	64.59	0.15	117.04
9	66.9	67.05	0.15	117.04
10	99.35	99.49	0.14	125.40
11	107.1	107.3	0.2	87.78

5. Conclusions

This study successfully introduces a traffic stream characteristics estimation system based on in-pavement sensor layout. The developed system will be durable since the sensors are packaged in GFRP material. The number of passed vehicle are tracked and counted for traffic flow estimation; with a higher sampling rate, the travel time of each vehicle is recorded with high accuracy. Then, speed (TMS and SMS) is estimated with previous knowledge of the distance between sensors. Future efforts will be applied to estimate traffic microscopic parameters (headway and spacing).

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