Single Variable-Constrained NDT Matching in Traffic Data Collection Using a Laser-Based Detector

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ABSTRACT As indispensable components of intelligent transportation systems, traffic detection and surveillance technologies deliver speed monitoring, traffic counting, and vehicle identification and classification. This paper proposes a normal distribution transform (NDT) algorithm to improve the speed accuracy and robustness of a laser-based detector. This method can deliver more accurate estimation of vehicle speed, enabling computation of the parameters of length and height. The results of simulation with different detector update rates suggest that the average estimation errors of vehicle parameters can be reduced using the NDT matching method, especially for the low detector update rate. The study also implemented a series of field experiments using the proposed detector prototype to verify the detector's measurements of vehicle parameters. The proposed method is a promising way in which to improve the laser-based traffic detector. In simulation test, initial experiments show that the accuracy of speed estimation can reach 95%, given the update rate of 1000 Hz for detector, the average length error can be reduced by approximately 60%. Even for speeding vehicles traveling at 150 km/h, the estimated speed error is limited to 10 km/h. In field test, for a vehicle at the speed of 80km/h, the estimation errors are within the threshold of the maximum errors of simulation, that is, 32 cm for length error and 5.71 km/h for speed error results.

INDEX TERMS Measurement by laser beam, measurement techniques, image matching, image registration, object detection.

I. INTRODUCTION

One of the critical issues for intelligent transportation systems (ITS) is the measurement of traffic flow parameters. This requires the acquisition of reliable real-time traffic information from highways, roads, and streets in metropolitan areas. Intelligent transportation systems (ITS) are highly dependent on the development of the Internet of Things (IoT) [1]. Sensor networks provide extensive dynamic and static traffic information, used to develop adequate traffic strategies, to improve traffic safety, to deliver logistics solutions, to increase transportation efficiency, or to meet civilian needs. Traffic detection sensors play a fundamental role in the IoT but are still under development.

An automatic non-intrusive traffic detection system can be used to acquire traffic information, identifying vehicles as they pass on a highway without interrupting traffic flow. The laser traffic detector proposed in this paper is a pattern recognition system that relies on data processing and feature extraction to recognize vehicle profile features. This detector can be used in applications such as auditing, manual and automatic fare collection processes, the generation of detailed vehicle statistics, and bridge/tunnel clearance verification.

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The various stationary traffic detectors are mainly classified into two categories: intrusive detectors and non-intrusive detectors. Intrusive detectors, including a loop detector and pneumatic road tubes and other weigh-in-motion devices, are not as easily installed or maintained due to their in-pavement location [2]. In contrast, non-intrusive detectors, such as video detection systems, microwave radar detectors, ultrasonic detectors, and passive/active infrared sensors, are installed above ground [3]. Each traffic detection solution has its own advantages and disadvantages. Considering the different user requirements, no detector has proved to be the optimal one.

Ultrasonic, infrared, and video imaging technologies are vulnerable to external noise. Video detectors are still widely used, as their cameras can capture abundant information about passing vehicles (size, color, license number, etc.), which is useful for vehicle identification. However, their performance degrades in bad weather conditions [4]. Alternatively, microwave radars are utilized as a reliable and cost-effective solution. Low-cost continuous wave (CW) radar, such as the road traffic microwave sensor (RTMS), determines the radial speed vectors of vehicles from the Doppler effect [5]. However, unless equipped with an auxiliary sensor, the CW Doppler radar sensors cannot detect vehicles that have stopped. In addition, CW Doppler microwave sensors perform poorly as volume counters at intersections where low-speed consecutive vehicles are not properly separated [6].

Laser sensors are robust in most environmental conditions, and can collect vehicle information for vehicle speed measurement [7]. It has been proven that detection accuracy by Lidar sensor alone is better than by camera on its own [24]. However, the laser reflective signal is sensitive to the surrounding environment and vehicle surface material, with the laser points usually sparse due to sampling frequency. In the traditional method, vehicle speed is calculated using different timestamps and predetermined distances between sensors. However, what remains challenging is how to choose the appropriate point in the collection of reflective points when calculating average speed. When using the beginning or ending point, the single point cannot guarantee its noise level: it is highly possible that the beginning point of the collection does not indicate the vehicle head edge. For the rest of the points, the corresponding relationship between two sets of collection data must be established. That is, a random point in Set 1 should associate with the point in Set 2 that represents the same point on the vehicle. Extracting a specific geometric feature is an alternative approach to solving the robustness problem in point matching [14]. However, the single line laser detector has inherent difficulties in acquiring sufficient features.

The laser detector, employing a laser range finder, has the capability to conduct vehicle profiling. Satyanarayana *et al.* [8] proposed a dual-purpose laser-based sensor configuration for vehicle classification which can be applied in a heterogeneous and lane-less traffic environment. Abdelbaki *et al.* [9] proposed a laser intensity image-based algorithm for automatic vehicle classification. Several similar detectors have been proposed. For instance, Cheng, Shaw *et al.* developed a detection system utilizing a pair of retro-reflective laser sensors [10]. However, the usage of these sensors may induce errors in practical implementation [11]. Li *et al.* [12] and Atluri *et al.* [13] developed detectors based on transmission-based laser sensors and delivered results with a high level of accuracy, but the proposed method is difficult to transform due to the lack of generalization ability.

In practice, the height of a vehicle is also an important parameter for traffic safety. It can be used to detect over-height vehicle infringements that may lead to incidents in which vehicles, typically trucks or double-decker buses, pass under a structure which is lower than the vehicle. Accidental collisions between over-height vehicles and bridge superstructures are a frequent phenomenon worldwide. The United States (US) Federal Highway Administration has reported that the third most common cause of bridge failure is vehicle or vessel collision [15]. In China, some researchers have focused attention on strikes caused by over-height vehicles [16]. These strikes lead to traffic delays, damage to bridge structures, bridge closures, and injuries. In worst-case scenarios, derailments, immediate collapse of bridge structures, and fatalities may occur [17].

On the other hand, height information is useful for vehicle classification. One can see that many classifications have distinguishable geometric shapes [18]. Urazghildiiev, D. *et al.* used two-dimensional (2D) longitudinal sections detected by a microwave radar sensor to classify vehicles [18]. This could achieve 95% accuracy in vehicle classification, provided the precise feature vectors were extracted, thus demonstrating that range-finder devices can provide precise vehicle parameters to support vehicle classification.

The current study focuses on the problem, when using a laser detector, of retrieving vehicle speed information and then computing the vehicle length. The normal distribution transform (NDT) method has demonstrated its benefits in terms of high robustness and efficiency in the range-finding system in extracting relative translation between contiguous scans [22]. However, the range-finding geometry model is different to this detector. The traditional NDT matching method is established on a manifold optimization, the solution is usually derived from a iteration form, such as Gauss Newton or Levenberg-Marquardt, the implementation scenario is different from our case. The application of the algorithm to the vehicle speed measurement is not technically sound. The NDT matching algorithm is modified to single variable constrained to measure the vehicle speed for the laser detector, deriving an approximation solution for the matching algorithm, with the acquired performance shown to be promising. Another research field focuses on three-dimensional (3D) vehicle reconstruction using cameras based on laser intensity collected by Lidar- Lite v3HP sensors [19], [20]. However, laser intensity is sensitive to the environment. If vehicle classification is the only motivation, a video

camera is neither technically necessary nor does it offer privacy protection. Moreover, the laser point-based method is highly dependent on the accuracy of the displacement measurement. Centimeter-level precision, at the very least, is required for a vehicle with speed exceeding 80 km/h [21] when estimating the height information necessary for vehicle classification. A statistics-based method is more robust and efficient [23] as it can reduce the contingency of measurement extremum. Inspired by this consequence, a histogram statistics-based method is developed to extract vehicle height profile in this study, and to validate the algorithm performance using bona fide experiment data. The contributions of this study are summarized as follows:

1) The developed prototype system, based on laser ranging sensors, couples profiling capability with a dual-detector configuration to permit speed measurement and vehicle recognition.

2) A method to infer vehicle speed using simplified NDT matching estimates the relative movement between two sensors that are recording.

3) A histogram statistics method is proposed to extract vehicle height and length profiles.

The remainder of this paper presents details on the development and analysis processes used in the study. Section 2 describes in detail the architecture of the proposed laser-based ranging sensor detector. Section 3 mainly describes the single variable NDT method used to estimate vehicle speed. A histogram illustrates the statistics technique for extracting vehicle height. The results of the simulation and field trials are presented in Sections 4 and 5, respectively. Finally, Section 6 delivers the concluding remarks.

II. SYSTEM ARCHITECTURE

The focus of the development stage was to realize the design in a real-world system that could be used for evaluation.

The detector consists of pairs of laser sensors, a microcontroller, and an industrial computer with software and Internet configuration. Every lane needs to deploy at least a pair of laser sensors, in parallel with vehicle flow. When operating, the two laser sensors l_1 and l_2 emit radiation vertically to measure the distance to the reflected surface in synchronization and at a high update rate. The presence of a vehicle will significantly decrease the measurement value. By simple subtraction, the height profiles of vehicles can be acquired. The proposed detection system architecture is presented in Fig. 1 below.

To meet practical requirements, the laser sensor should have a considerable operational range and update rate. The laser range finder used is Lidar-Lite v3HP. It can operate at a higher update rate (typically greater than 1000 Hz) over a longer range (> 10 m) than its predecessor [25]. In addition, high-frequency ranging, high-precision timing, and synchronal processing require a robust processor.

The current study's intention is also to create a platform upon which the code could be developed. In the initial prototype design, the system utilizes an open-source Arduino
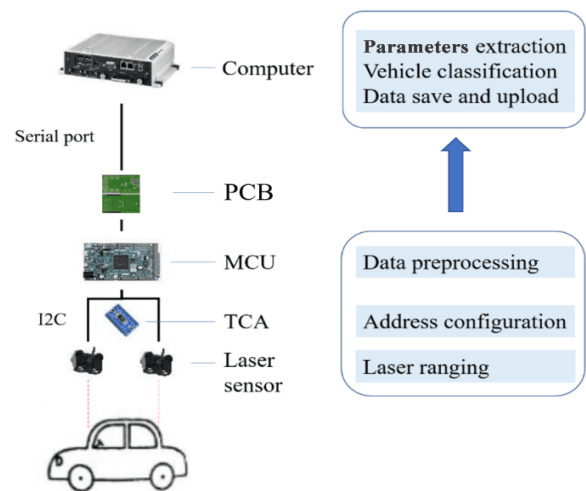

FIGURE 1. System architecture.

MCU (microcontroller) [26]. The prototype has an auxiliary module that consists of a SD card data logger. It is functional and works continuously on broad. The MCU records on microsecond level corresponding to every displacement measured by the laser sensors, which are connected via standard I2C wiring. To achieve synchronal timing, several sensor pairs need to operate on the same I2C bus. An I2C switch, the TCA9548A module, is used to assign varied addresses [27]. Consequently, a newly designed printed circuit board is applied to connect the MCU to the personal computer (PC). The microsecond timestamps, $t^1(n)$ and $t^2(n)$, of the two sensors are recorded, corresponding to every measured altitude, $h^1(n)$ and $h^2(n)$, of the vehicle surface. Let $n = 1, \ldots, N$, with N being the number of output samples. The data are transmitted to the upper computer via a serial port. Simultaneously, a PC program is used to estimate vehicle parameters and to classify vehicles. The problem can be formulated as follows: given the observations, $h^1(n)$, $h^2(n)$, $t^1(n)$ and $t^2(n)$, estimate the parameters of a vehicle and classify it. The estimates of vehicle parameters, including speed and shape, can be acquired in different ways. Due to uncertainty about the sensor's update rate, the recorded timestamp may have a considerable degree of error. For example, estimated arrival time $t(1)$ will be a little later than the true arrival time t_{arrive} (see Fig. 2). The same happens when the vehicle departs. Errors may partly counterbalance each other at both ends of the detector. Nevertheless, considerable errors may occur, particularly for high-speed vehicles. Cheng took the mean value of arrival and departure of the two sensors as the estimated speed [10], as a response to the detector being able to recognize only the front and rear of a vehicle.

The vehicle's acceleration is an optional item to be considered. Usually, acceleration is negligible during the displacement of one vehicle length. In contrast, the proposed detector can acquire an entire profile of vehicle height and length. It is reasonable to believe that additional recognized probe points of a vehicle's surface can reduce estimation error.
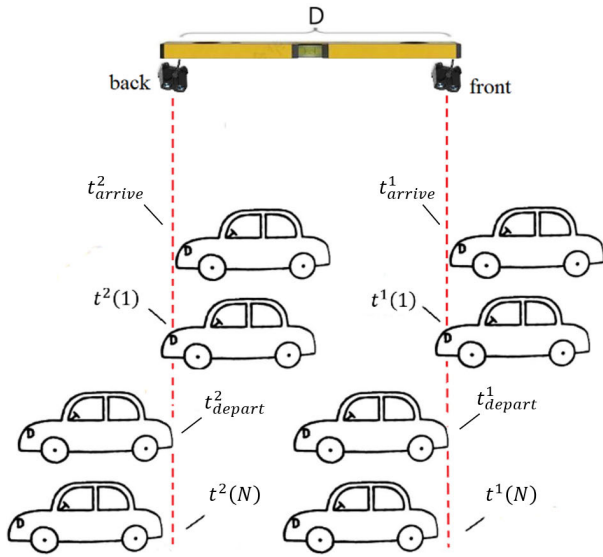
FIGURE 2. Detector system operation.

III. METHODOLOGY

The laser detector is a kind of range sensor, with the output points a set of spatial sample points from a vehicle's surface. Using the points to represent a vehicle in a straightforward way has these limitations: the points for the vehicle's surface are insufficient although the detector's sampling rate is considerable, and points merely mean less without the surface characteristic.

A. NDT-BASED VEHICLE SPEED ESTIMATION

The normal distribution transform maps cluster points to a compact smooth surface representation, and then describes each set of points with probability density functions (PDFs). The vehicle speed calculation can be transformed into a maximum probability problem. For the proposed method, the first step is to divide the points into a grid of cells. A higher grid resolution can improve the matching accuracy and reliability, but it will also increase the computation required.

Taking the sampling data from the first detector, for instance, the horizontal axis is the index number of reflective points, and the vertical axis is the height of the object. No rigorous rules or regulations are followed when setting the cell resolution for a typical NDT implementation. The optimal resolution is usually achieved after conducting a mass data test or statistical analysis. In the current study, the authors consider the following two cases: (1) in many Lidar NDT tests, the cell size is empirically set to 1 m by 1 m while, in the field test, a passenger car of approximately five meters (m) is used. Therefore, the horizontal axis is divided into five cells. (2) The 2D space consists of cells some of which are empty due to the dimensions of the vehicle profile. At a minimum, half the cells should have data for collection. The y-axis is divided into five cells by rule of thumb. Finally, the resolution is assumed to be five by five cells; hence, the data points are stratified into 25 grids, as shown in Fig. 3. Considering the
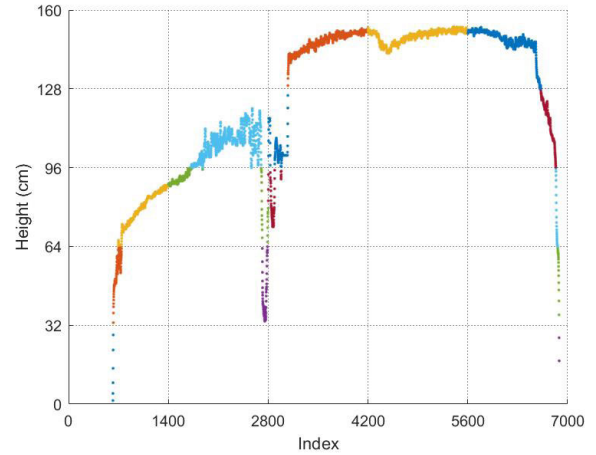

FIGURE 3. Sampling points of the first laser sensor.

shape of the vehicle profile, five by five grids can represent the local point distribution for the detector.

Assuming that the fall of the points in each cell follows a Gaussian normal distribution, the mean and covariance of the parameters can be computed by:

$$\mu = \frac{1}{m} \sum_{k=1}^{m} y_k \tag{1}$$

$$\sigma = \frac{1}{m-1} \sum_{k=1}^{m} (y_k - \mu)(y_k - \mu)^T \tag{2}$$

where $y_{k=1,2...m}$ represents the positions of laser points in one cell. For a measured point x, its likelihood is given as:

$$p(x) = \frac{1}{(2\pi)^{1/2}\sqrt{|\sigma|}} \exp(-\frac{(x-\mu)^T \sigma^{-1}(x-\mu)}{2}) \tag{3}$$

In each cell, the PDF is the representation of local characteristics, including the center position and distribution trend. The corresponding confidence ellipses of each cell are shown in Fig 4. It should be noted that if the points in one cell are nearly colinear, the covariance σ tends to be singular: it cannot be inverted when calculating the likelihood function p. Therefore, the cells with less than five points are discarded and if one of the eigenvalues λ_1 is 100 times larger than another λ_2, λ_2 is forced $\lambda_2 = 0.01\lambda_1$ into a matching process.

When using the NDT method for the traditional registration problem, the 2D information is usually same. For example, in laser odometer scan matching, x and y represent the north and east orientation in Cartesian coordinates, with the range units equivalent to each other. However, in our research problem, the horizontal orientation is the sampling index sequence of the detector while, for vertical orientation, it is the height of vehicle. That is, the horizontal range number is more than a dozen times that of the vertical range number. This can easily cause great differences in the eigenvalues of the PDF covariance. Hence, in our algorithm, the authors scale the horizontal number to an appropriate scope to avoid this issue. The goal of the matching process is to find the pose which transforms the current
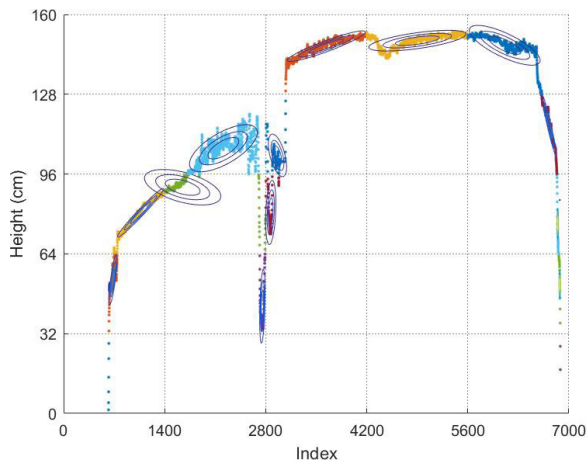
FIGURE 4. Likelihood of ellipses of divided cells.

point position into a reference frame to maximize likelihood. In this research problem, the authors assume that the vehicle displacement in vertical orientation can be ignored when crossing the detected area. The authors do not consider the rotation parameter. This is reasonable for a typical 0.5-m-length detector as the detector is usually deployed in a flat place and the vehicle heading orientation is maintained in a straight line when crossing the detected area. Hence, the pose transformation between two laser sensors is degenerated into only horizontal displacement, that is, $T(x) = x_{cur} + \Delta x$, where x_{cur} is the sampling point for Laser 2, and Δx is the number of displacement index numbers to be estimated from the matching optimization.

For a given (initialization), $T(x)$ makes a transformed position in Δx the reference frame: the cell grid to which it belongs can thus be determined, according to the new position. For a set of points, $X = \{x_1, x_2, \ldots x_m\}$, after implementing the transformation T, for each mapped point, the likelihood can be given by Eq. 6, depending on the normal distribution parameters of the cell in which it falls. The best Δx is the one that can maximize the objective function below.

$$\max_{x \in \mathbb{R}^1} s(x) = \sum_{k=1}^{n} p(T(x, x)) \tag{4}$$

The matching problem is then changed into the optimization issue. As Δx is only a one-dimension variable, the maximum value can be achieved by using a simple gradient algorithm. The gradient of s as a function of x is:

$$g(x) = \frac{\partial s}{\partial p} = \sum_{k=1}^{n} x_k \sigma_k^{-1} \frac{\partial T}{\partial \Delta x} \exp(-\frac{1}{2} x_k^T \sigma_k^{-1} x_k) \tag{5}$$

where $\widetilde{x}_k = T(x) - \mu$, $\frac{\partial p}{\partial \Delta x}$ is the first-order derivative of the likelihood with respect to Δx. For the given set X, each entry is a 2D planar point that can be represented as $x_i = [p_x \ p_y]$, and as aforementioned in the single variable-constrained algorithm, the optimization only focuses on the horizontal component p_x, with Δx regarded as $\Delta x = [\Delta p_x \ 0]$; thus:

$$\frac{\partial T}{\partial \Delta x} = \begin{bmatrix} \frac{\partial p_x}{\partial \Delta x} & \frac{\partial p_y}{\partial \Delta x} \end{bmatrix} = [1 \ 0] \tag{6}$$

Algorithm 1

Single variable-constrained NDT

For two laser sensors' collection X and Y, scale the horizontal coordinate to a range of 0–200

1: {Initialization}

2: Divide and allocate 5 by 5 structure $B = \{b_1, b_2, \ldots b_{25}\}$ for reference collection Y

3: **for** all points $y_{k=1,2,\ldots m}$ in Laser 1 collection, **do**

4:     find cell b_i that contains y_k

5:     store the index of b_i and y_k

6: **end for**

7: for all cells $b_i \in B$ **do**

8:     to all points y_k^i in b_i, compute the likelihood parameter

9:     $\mu = \frac{1}{m} \sum_{k=1}^{m} y_k$

10:     $\sigma = \frac{1}{m-1} \sum_{k=1}^{m} (y_k - \mu)(y_k - \mu)^T$

11: **end for**

12: {Matching}

13: $\Delta x = 0$

14: **While** not converged **do**

15: **for** all points $x_{k=1,2,\ldots m}$ in Laser 2 collection **do**

16: determine the cell b_i that contains $T(x, \Delta x) = x_k + \Delta x$

17: if b_i is empty without μ_i, σ_i, return 15

18:     compute the gradient g_k of each mapped x_k

19:     get the sum of gradient $g_{sum} \sum g_k$

20: **end for**

21: **update** $\Delta x = \Delta x - \alpha \cdot g_{sum}(\Delta x)$

22: **end while**

23: convert Δx into the number of samples and then obtain the vehicle speed.

The desired Δx can be obtained by iterating the single variable Δx until it converges:

$$\Delta x = \Delta x - \alpha \cdot g(\Delta x) \tag{7}$$

where α is a constant step length that can be empirically determined: in this algorithm, we set $\alpha = 0.1$. Once Δx is obtained, the vehicle speed can be given as:

$$V = \frac{D}{\Delta x * \Delta t} \tag{8}$$

where

D = the distance between the two sensors l_1 and l_2;

Δt = the time interval between adjacent sampling points.

The pseudo code of this algorithm is summarized as follows:

B. HEIGHT AND LENGTH ESTIMATION

A more robust vehicle parameter estimation technique, based on extracting height and length profiles, is proposed in this paper. The basic idea is to identify vehicles' potential flat surfaces to acquire a larger reference point set S from which to calculate vehicle parameters. The basic assumption is that the measurement error of $h(n)$ is negligible.

For each of the two sensors, a frequency histogram of vehicle height as $F(g_i)$, $i = 1, 2, \ldots F(g_i)$ is created, with this defined as the percentage of $h(n)$ that is divided in the interval $[g_i − \Delta/2, g_i + \Delta/2]$, where $\Delta = g_{i+1} − g_i$. A peak at point $\hat{g}$ in the histogram means a flat surface on the vehicle, with probe points included on this surface. In practice, vehicles commonly have several flat surfaces which mean that local peaks occur in frequency histograms. The vehicle height H can be estimated as:

$$H = \frac{1}{2} \times \left(\widehat{g^1} + g^2 \right) \qquad (9)$$

where $\widehat{g^1}$ and g^2 are the surface height of the frequency histograms of l^1 and l^2 at the maximized frequency, respectively. In addition, $F(H) \geq C$ is required, where C represents a threshold of the flat surface's length. Let $h(n)$, $n = M, M + 1, \ldots, M + K$ be the observations of the highest surface (vehicle roof), with this accompanied by the recorded timestamps $t(n)$. The first and last points, $t(M)$ and $t(M + 1)$, as well as four quantile points $t(M + K/4)$, $t(M + K/2)$ and $t(M + K \times 3/4)$ are added to reference point set S. The front and rear of vehicles are also considered. The vehicle speed can be estimated as Eq. (8). Hence, the vehicle length L can be estimated as Eq. (10):

$$L = \frac{1}{2} \times V \times (t^1(N) − t^1(1) + t^2(N) − t^2(1)) \qquad (10)$$

Consequently, after extracting the profiles of the vehicle roof, the estimates of vehicle parameters are obtained, including speed V, height H, and length L. The vehicle classification can be based on the vehicle shape. Urazghildiiev, I. R. *et al.* proposed a classification algorithm based on the full height and length profiles of vehicles [28]. If the precision of the estimation is sufficient, most vehicles can be classified, based on height H and length L, when relatively general classification schemes are introduced [18].

IV. SIMULATIONS

The simulation is designed to verify the NDT speed measurement performance. Errors arose from the timing difference in the gap between the recorded timestamps and the true timestamps due to discrete sampling of the laser sensor. These errors related to the vehicle speed and the update rate of the laser sensors [11]. When the update rate for the laser sensor is fixed, if the vehicle travels at a high speed, the result is lower sampled points for the detector. To evaluate measurement performance using the proposed methodologies in different cases, two simulation tests were conducted to study the correlation between the average speed estimate error and the vehicle speed, under different detector update rates. The first simulation estimates spot speed and vehicle length, according to the traditional method by computing the beginning and ending point time interval. In contrast, the second simulation estimates the same measurements with the proposed modified NDT algorithm.

The simulations are configured by MATLAB. The laser update rate is set to range from 100–1000 Hz with the

constant increment of 10 Hz. To simulate the vehicle trajectory, the arrival of the vehicle is assumed to follow the Poisson distribution in any millisecond [29]. The sample size of each simulation is set to 100,000. The vehicle in the simulation is sampled randomly from a dataset of 206 vehicles of different sizes. The speed of the vehicle is assumed to follow an empirical cumulative distribution. The distribution is based on 50 hours of data obtained by frequency modulated continuous wave (FMCW) radar on a section of urban arterial road in Beijing. The vehicle is assumed to travel at a constant speed when passing by the detector, with the distance between the two lasers, $°D$, set to 0.5 m.

The variables of the above-mentioned random processes are independent from each other. Our study assumes that the vehicle roof has a random start position, end position, and altitude to the hood. The detector operates in an ideal state; that is, the deviation of displacement measurement by the lasers is zero, guaranteeing that relatively accurate profiles can be obtained.

In the first simulation estimates, the average vehicle speeds and vehicle lengths estimation errors are shown in Fig. 5. This shows that an increase in the update rate or a decrease in vehicle speed will lead to a reduction in estimation errors. A power-law fitting is applied to the samples using the MATLAB fitting toolbox $R^2 = 0.99$. The long-tail distribution fitting indicates the errors will drop sharply with the increase of the update rate, but the errors will still persist. Due to the maximum update rate of the laser rangefinders, the simulation indicates the device delivers some speed estimation errors that is a function of incoming vehicle speed.

Owing to the resolution limitation of the millisecond-level timer on board, the maximum update rate is 1000 Hz. With typical vehicles traveling at 80km/h on highways, a 1000 Hz update rate can hold the average error of vehicle length to less than 15 cm.

In the second simulation estimates, the same settings were used for vehicle trajectories and the detector scanning operation. The NDT matching-based algorithm simulation results are shown in Fig. 6. Comparing this method's results to the traditional method's results in the first simulation (see Fig. 5), the algorithm significantly reduces the average estimate error for both vehicle speed and length. At the same time, the algorithm is more robust against increases in vehicle speed. Given the update rate of 1000 Hz, the average length error can be reduced by approximately 60%. Even for speeding vehicles traveling at 150 km/h, the estimated speed error is limited to 10 km/h (see Table 1).

V. FIELD TESTS

The field experiments were carried out on an urban road under construction in Cangzhou, Hebei province, China. The detector was mounted on a horizontal gantry approximately 3.4 meters above the pavement for convenience (see Fig. 7). A leveling ruler was used, with the laser sensors on both ends, to ensure that the laser radiation would emit vertically to the lane below; the ruler was also aligned with the direction of
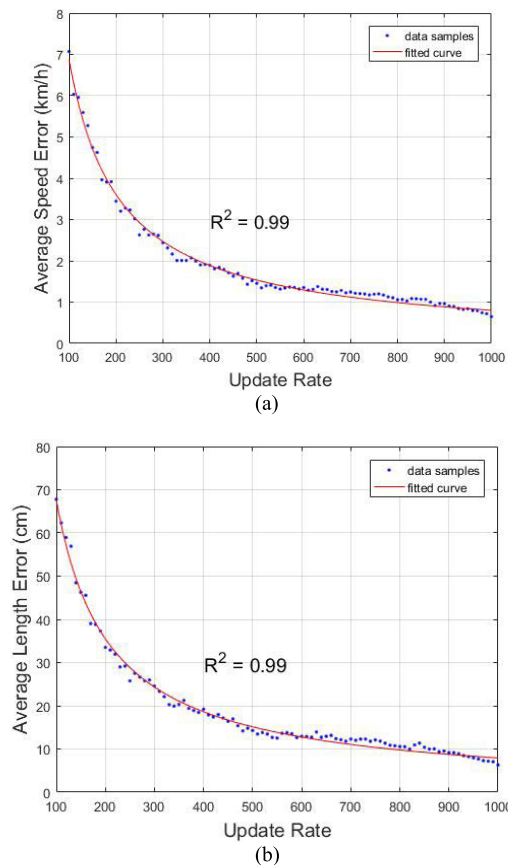
FIGURE 5. Results of first simulation: (a) estimated speed error, (b) estimated length error).

TABLE 1. Maximum errors of second simulation.

Speed (km/h)	Maximum length error (cm)			Maximum speed error (km/h)		
	400 Hz	700 Hz	1000 Hz	400 Hz	700 Hz	1000 Hz
30	28	17	8	2.00	1.29	0.62
60	41	26	9	5.67	3.29	1.07
80	56	32	11	10.00	5.71	1.82
120	76	52	25	19.00	13.12	6.50
150	98	66	33	30.88	20.43	9.54

the road. An invar caliber rule was then used to measure the distance between the two sensors, with a laptop used to process data and estimate vehicle parameters. The gap, namely, D, between the two-laser rangefinder is a constant value. As D is as short as 50 cm, the assumption is reasonable that the pose of high-speed vehicle is to keep constant when traveling through the short-length gantry. In the field, a sedan was traveling straightforward through the narrow width gantry equipped with a global positioning system (GPS) set and its antenna mounted on top of the vehicle. Particularly, the experiment was focused on the high-speed scenario as the simulations suggest the high-speed scenario that is most adversary one for speed measurement precision.
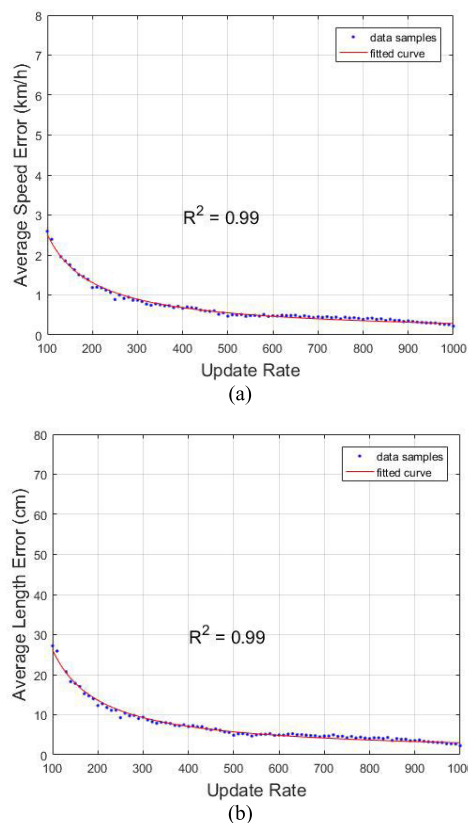

FIGURE 6. Results of second simulation. (a) estimated speed error, (b) estimated length error).

FIGURE 7. Experimental site and detector prototype.

According to the manual of the laser rangefinder, the update rate can reach 1000 Hz. However, the update rate is subject to the capacity of MCU processing. According to the time measurement by on-board ceramic resonator, the update rate is approximately 700 Hz in the field. A GPS module, NEO-6M (u-blox), was used to record the spot speed of the passing vehicle [30]. According to the manual of the manufacturer, the accuracy of GPS speed measurement can

TABLE 2. Experimental results.

Estimated value	Speed (km/h)	79.04	77.16	80.75	74.14
	Length (cm)	498	445	465	454
	Height (cm)	130	137	97	154
True value	Speed (km/h)	77.51	76.86	76.57	76.39
	Length (cm)		487		
	Height (cm)		147		
Error	Speed error (km/h)	1.53	0.30	4.18	2.25
	Length error (cm)	11	42	22	33

reach 0.1 m/s (equivalent to 0.36 km/h), with this acceptable as the true value as the vehicle dynamic is relatively low. The surrounding area has good clearance without major obstacles. Moreover, as the number of visible satellites is between seven and eight, and the geometric dilution of precision (GDOP) is low. The quality of speed measurement results can be guaranteed.

The vehicle speed and length are estimated by the proposed method. The average speed error is 2.09 km/h, the average length error is 27 cm, and the average height error is 17.5 cm (see Table 2). Although the amount of data is not sufficient to verify the proposed method through the simulation results, the measurement errors of these tests are to be expected. The estimation errors are within the threshold of the maximum errors of simulation, that is, 32 cm for length error and 5.71 km/h for speed error results (Table 1).

In the first height estimation, we use the minimum echo distance value as the vehicle height, with outliers found in the estimated height values. With the increase of the ranging distance, the laser decreases in terms of reflective power [25]. These factors led to the failure to collect a full vehicle profile. To improve the accuracy and robustness of the height estimation, another field experiment was conducted, using the statistic histogram method. A typical example of height profiles provided by the detector is shown below in Fig. 8.

The corresponding normalized histograms of the two lasers are shown in Fig. 9. The histogram's highest bin represents the sample data of the vehicle roof. The frequency threshold C is set to 0.15. For Laser 1, as $F\left(\hat{g} = 145\right) > F\left(\hat{g} = 103\right) > C$, the bin value $\hat{g} = 145 \, cm$ is accepted as the roof of the vehicle. A similar process is conducted for Laser 2.

The vehicle parameters are then estimated according to (3) and (4). Several tests are conducted (see Table 3). The proposed statistic method can significantly reduce estimate error.
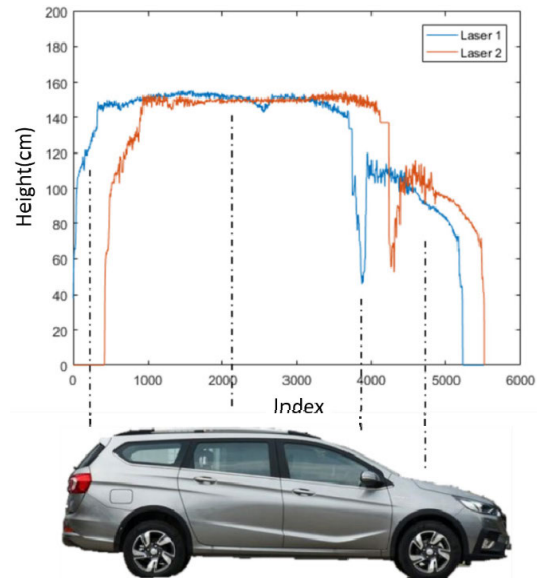

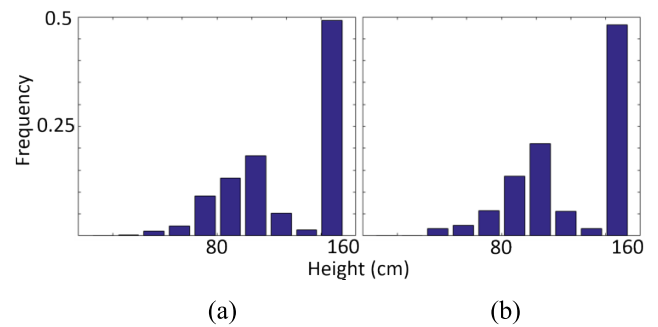**FIGURE 8.** Comparison of obtained profiles and vehicle.

FIGURE 9. Comparison of obtained profiles and vehicle: (a) Laser 1, (b) Laser 2.

TABLE 3. Test results.

No.	Vehicle height (cm)	Minimum echo distance estimation		Proposed statistic histogram estimation	
		Height (cm)	Height error (cm)	Height (cm)	Height error (cm)
1		184.3	32.3	164.9	12.9
2		170.2	18.2	157.6	5.6
3		195.8	43.8	164.7	12.7
4		190.2	38.2	170.7	18.7
5	152	177.1	25.1	166.3	14.3
6		191.8	39.8	156.3	4.3
7		182.4	30.4	169.6	17.6
8		171.4	19.4	162.9	10.9

VI. CONCLUSION

Intelligent transportation systems (ITS) require various types of fundamental traffic information. The laser detector has its advantages in accuracy and cost effectiveness. In the study described in this paper, a laser-based traffic detector

has been developed, with a single variable-constrained NDT matching method proposed. The aim is to aid in computing vehicle parameters including speed, length, and height, with these collected to avoid potential over-height vehicle collisions with structures. The device is based on open-source hardware and, in terms of affordability, can be reproduced. Moreover, the configuration provides users with versatility in applying the device. For instance, a single unit can work independently for a single lane, while multiple units can be integrated for multiple lanes. The proposed device enables a common research hardware platform, while the open-source code demonstrates a transparent algorithm for vehicle height and length measurement, with the results able to be used for vehicle classification and for further enhancement.

The development of advanced laser sensors provides motivation for the improvement of traffic laser detection systems. The simulation results validate the speed and length estimations showing that the algorithm can significantly reduce errors, with the average error of vehicle length estimation at the decimeter level. Our study's field experiment verified that the errors of the proposed detector are within the simulated precision level.

The method is promising for future application. The device is compact and easily installed. Moreover, the versatile configuration enables the device to be either a one-lane unit or a multiple-lane unit. As the laser-based detector is based on open-source hardware, not only it is affordable, but it can be customized in other studies exploring the development of localized detectors.

Considering the limited size of these field tests, future research could scale up the experiments. The next research step would be to use a reliable source to further evaluate the detector data and vehicle classifications.

The current open-source platform components need to be improved in terms of precision and resolution. The current crystal oscillator on board can only offer a millisecond level of resolution. The laser sensor failed to measure distance precisely over a long detection distance or at a high update rate. More improvements need to be made to the laser detector to verify the proposed NDT matching speed measurement method.

Some external factors, such as the detector's alignment, would lead to the downgrading of detector results. Taking into consideration the application's convenience, the entire detector needs to be packaged with its reliability tested in a harsh environment. In addition, the open-source hardware provides a compatibility platform for data fusion with different sensors. As the Doppler radar is more appropriate for higher speed traffic, other future research could involve the fusion of radar and laser sensors.

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