Research Article

Can Autonomous Vehicles Save Fuel? Findings from Field Experiments

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The majority of the more recent studies have mainly focused on how to achieve energy-efficient goals by optimizing the driving behavior for human-driven vehicles or designing trajectory planning and tacking algorithms for autonomous vehicles. However, the energy-saving advantages of autonomous vehicles have not been quantitatively and theoretically explored. Therefore, this study aims to specifically clarify whether autonomous vehicles use less fuel than human-driven ones. First, the differences in driving behavior, regarding speed control, between autonomous vehicles and human-driven vehicles were compared. The most notable difference between them is that an autonomous vehicle can control the vehicle speed more effectively, with less speed fluctuations than a human driver. Subsequently, the influence of speed fluctuation on vehicle fuel consumption (L/100km) was formulated based on the vehicle specific power (VSP) model. The mathematical deduction showed that the fuel consumption is proportional to the speed fluctuation under the same mean speed. Finally, simulation experiments were conducted under real scenarios. The simulation data showed that the fuel consumption increases almost linearly with the increase in speed fluctuation. Field experiments were also conducted on the fuel consumption of an autonomous vehicle under different driving modes. The experimental data showed that the fuel consumption also increases almost linearly with the increase in speed fluctuation. In the human-driven mode, the fuel consumption increased by 5.6% and 14.7%, respectively, compared with that in the autonomous mode at average speeds of 20 km/h and 40 km/h. Furthermore, the maximum fuel consumption was up to 60% more when the autonomous vehicle was driven by a driver, as the driving behavior displayed greater speed fluctuations.

1. Introduction

Energy shortage and environmental issues have become increasingly severe worldwide. Related pieces of literature show that the transportation sector was responsible for approximately 59% of the total oil consumption [1], and approximately 22% of the carbon dioxide emissions in 2011 [2]. In 2015, the transportation sector generated nearly 30% of all greenhouse gas (GHG) emissions [3]. Emissions from transportation are increasingly being considered as the major contributor to the onset of global warming and the decline in the quality of life and health of individuals. The automobile industry is correspondingly experiencing pressure owing to the oil shortage crisis and environmental protection requirements [4]. Therefore, there is an urgent need to control and reduce the fuel consumption of the automobile sector to mitigate the energy crisis, as well as air pollution and related issues.

Hence, reducing vehicle fuel consumption has attracted considerable attention. Generally, the factors affecting fuel consumption include many aspects, such as the characteristics of the vehicles (e.g., the mass, load, engine type, and power consumption of on-board accessories), the road conditions (e.g., pavement roughness, road gradient, and geometry), and the environment (e.g., weather conditions, temperature, and traffic flow situation) [5].

Apart from these factors, driving behavior optimization of human-driven vehicles is considered by many researchers as the main measure used to reduce fuel consumption, which is also known as eco-driving. Driving behavior is commonly represented by the vehicle speed and its derivatives [6]. It is commonly known that fuel usage (L/100 km) varies significantly with different speed ranges. Xu et al. [7] developed a novel computational approach to accurately estimate the fuel consumption of heavy trucks. Those authors found that
the fuel consumption of trucks was positively correlated with speed fluctuation and acceleration share. Specifically, less fuel was consumed during cruising and deceleration. Significant oscillations or accelerations are associated with the highest fuel consumption. Data-mining technology has also been used to investigate the extent to which different driving styles negatively or positively affect fuel consumption [8]. Toledo and Shiftan [9] evaluated the effectiveness of the feedback given to drivers to change their driving behavior, with the aim of improving safety, and reducing fuel consumption and emissions. Feedback was provided using in-vehicle data recorders (IVDR). Their results showed that IVDR feedback improved driver behavior and reduced fuel consumption by a certain percentage. Wu et al. [10] proposed an ecologically driven support platform based on Internet+ technology to realize real-time dynamic acquisition and feedback optimization of driving behaviors. Almannaa et al. [11] conducted a controlled field experiment designed to evaluate the efficiency of a speed-recommendation algorithm developed to reduce vehicle fuel consumption at signalized intersections. The experimental results showed that speed advisory to the driver via vehicle-to-infrastructure communication (V2I) can reduce fuel consumption and travel time by 19% and 10%, respectively, compared to the scenario without V2I. The above-mentioned researches shed light on energy conservation and emission reduction; however, they only qualitatively note that there is a positive correlation between fuel consumption and speed fluctuation under human-driven environment.

Recently, autonomous vehicles are regarded as a new technological breakthrough in ensuring roadway safety and have the potential to decrease traffic congestion, increase mobility, and reduce fuel consumption [12]. Specifically, trajectory planning and tracking are the main measures used to reduce fuel consumption. Li et al. [13, 14] proposed a simplified model that can control the overall smoothness of a platoon of connected automated vehicles and optimize traffic performance in terms of fuel efficiency and driving comfort. Yao et al. [15] proposed a trajectory-smoothing method based on individual variable speed limits with location optimization in coordination with prefixed traffic signals. The results show that this method greatly increased traffic efficiency and reduced fuel consumption. Ntousakis et al. [16] presented a trajectory planning methodology to achieve safe and traffic-efficient merging of vehicles on highways, while minimizing the engine effort and passenger discomfort through the minimization of acceleration and its first and second derivatives during the merging maneuver. And the simulation results proved the applicability and effectiveness of the method. Although these studies provide literature to energy-saving under autonomous environment, the quantitative relationship between the fuel consumption and speed fluctuation is still not theoretically explored. This research presents a mathematical deduction to unveil the relationship between fuel consumption and speed fluctuation. The information gained from this study can be used as the theoretical support of the energy-efficient based driving behavior optimization for human-driven vehicles as well as trajectory planning and tracking for autonomous vehicles, which distinguishes this study from the above-mentioned researches.

The remainder of this paper is organized as follows: Section 2 presents the methodology in which theoretical deductions are performed based on the VSP model, Section 3 presents the experiments and a discussion of the benefits and applications, and the paper ends with concluding remarks in Section 4.

2. Methodology

2.1. Research Framework. The overall framework of this study is shown in Figure 1 and involves the following tasks.

Task 1: Compare the difference in driving behavior, regarding speed control, between autonomous vehicles, and human-driven vehicles. Additionally, analyze the basic principle of controllers of autonomous and human-driven vehicles while maintaining speed. The significant difference between them is that an autonomous vehicle can better control the speed, with fewer fluctuations than a human driver.

Task 2: Conduct theoretical correlation modeling between fuel consumption and speed fluctuation. This study proposes the hypothesis that speed fluctuation may be an important factor affecting fuel consumption. To quantitatively deduce the relationship between fuel consumption and speed fluctuation theoretically, this study selected the representative VSP model, which is a physical principle-based fuel consumption model. The speed signal used in the VSP model is abstracted as a triangular wave signal, and the speed fluctuation is characterized by speed variance [17]. VSP is defined as the instantaneous power requirement of a vehicle; therefore, fuel consumption can be derived as the integral of VSP over time. Consequently, the influence of speed fluctuation on vehicle fuel consumption is equivalent to the relationship between the result of integration and speed variance.

Task 3: Perform experimental verification, including the simulation experiment and the field experiment, by taking advantage of real-time in-vehicle data. Simulation experiments were conducted using a moving average filter to generate driving cycles with different speed variances from the real scenario. Field experiments were carried out with an autonomous vehicle under two driving modes: autonomous and human-driven. For the human-driven mode, experiments were conducted three times, with different speed fluctuations, and the resulting fuel consumption was compared with that under the autonomous mode.

2.2. The Difference between Human and Autonomous Driving Behavior. Both autonomous and human-driven vehicles have similar speed control principles. For autonomous vehicles, the input for the controller includes the difference between the current vehicle velocity and its expected value, and the information from equipped sensors, such as cameras and LiDAR. For human-driven vehicles, the input information supporting speed control comprises the velocity difference between the measured and expected values, as well as the information perceived by drivers. The actuators are the brake and throttle pedals, which are the same for both
autonomous and human-driven vehicles. Figure 2 shows the basic principle of a controller for maintaining a particular speed.

The significant difference between automated and human-driving modes is that an autonomous vehicle can better control the speed resulting in fewer speed fluctuations than a human driver. For a human driver, many uncertain factors such as the driver’s gender, age, character, driving experience, reaction time, and fatigue degree, as well as the weather and illumination conditions, will affect driving stability. Accordingly, it is impossible for a human driver to control the vehicle speed constantly and precisely, which will inevitably lead to “stop-and-go” driving behaviors. In contrast, an autonomous vehicle is controlled by electronic and mechanical devices using a dedicated feedback control algorithm. As a result, its speed can be stabilized at a desired level with lower errors.

2.3. The Relationship between Speed Fluctuations and Fuel Consumption. The VSP model was first proposed by Jiménez-Palacios (1999) to reflect the close relationship between vehicle power requirements and vehicle dynamics [18]. It represents the engine load against the acceleration resistance (kinetic energy), rolling resistance, climbing resistance (potential energy), and aerodynamic drag. A simplified expression of VSP was also provided by Jiménez-Palacios (1999), as shown in the following equation:

\[ VSP = \alpha \cdot v \cdot a + \beta \cdot v + \gamma \cdot v^3, \]  

where \( \alpha, \beta, \gamma \) are the calibration coefficients; \( v \) is the vehicle speed; and \( a \) is the vehicle acceleration.

The VSP model has the advantages of not only showing vehicle dynamics, but also explicitly reflecting the dynamic relationship between fuel consumption and driving behaviors (vehicular speed and vehicular acceleration). As mentioned above, the VSP is defined as the instantaneous power requirement of a vehicle. The power is derived from the energy released by fuel combustion. The energy released by fuel combustion is converted into the rotational kinetic energy of the driving wheels through the drivetrain systems, and the rotational kinetic energy is eventually converted into the translational kinetic energy of the vehicle. At the same time, some energy is used to overcome the above-mentioned resistance and perform the work. Therefore, fuel consumption can be derived as the integral of the VSP over time, as shown in the following equation:

\[ \text{Fuel} = \int_{t_s}^{t_e} VSP \, dt = \int_{t_s}^{t_e} \left( \alpha \cdot v \cdot a + \beta \cdot v + \gamma \cdot v^3 \right) dt, \]  

where \( t_s \) is the start time, and \( t_e \) is the end time. Assume that \( OD \) is any segment of a cruise process, \( O \) is the origin point, and \( D \) is the destination point. When the vehicle is traveling from \( O \) to \( D \), there are slight fluctuations in the speed, which is associated with many micro-driving behaviors, including acceleration and deceleration.

In this study, the \( OD \) journey was abstracted as one cycle of a triangular wave, as shown in Figure 3, in which \( V_e \) represents the expected value and \( \delta \) represents the fluctuation component. The vehicle speed fluctuates around \( V_e \).
Considering that the variance of a triangular signal is equal to half of the square of the signal amplitude, that is, $\delta^2/2$, the influence of speed fluctuation on fuel consumption is equivalent to the influence of the triangular signal variance on fuel consumption. As noted in equation (1), the VSP can be expressed as a function of vehicle speed and acceleration, and acceleration is the first derivative of speed. Therefore, the triangular signal can be substituted in equation (2) to directly model the relationship between fuel consumption and speed fluctuation.

As shown in Figure 3, one cycle of a triangular wave can be divided into three parts, whose acceleration speed, time, and speed fluctuation are denoted as $a_1$, $a_2$, $a_3$; $t_1$, $t_2$, $t_3$; and $s_1$, $s_2$, $s_3$, respectively, as shown in the following equation:

$$
\begin{align*}
&\begin{cases}
  a_1 = a (a > 0), \\
  a_2 = -a, \\
  a_3 = a,
\end{cases} \\
&\begin{cases}
  t_1 = \frac{\delta}{a}, \\
  t_2 = \frac{2\delta}{a}, \\
  t_3 = \frac{\delta}{a},
\end{cases} \\
&\begin{cases}
  s_1 = \frac{(V_e + \delta)^2 - V_e^2}{2a}, \\
  s_2 = \frac{(V_e - \delta)^2 - (V_e + \delta)^2}{2a} = \frac{2V_e\delta}{a}, \\
  s_3 = \frac{V_e^2 - (V_e - \delta)^2}{2a} = \frac{2V_e\delta - \delta^2}{2a}.
\end{cases}
\end{align*}
$$

The total time consumed $T$ and total mileage $S$ are as follows:

$$
\begin{align*}
&T = t_1 + t_2 + t_3 \\
&= \frac{4\delta}{a}, \\
&S = s_1 + s_2 + s_3 \\
&= 4V_e\delta.
\end{align*}
$$

According to equation (4), VSP ($t$) can be decomposed into three parts, as shown in the following equation:

$$
VSP(t) = P_{\text{kinetic}}(t) + P_{\text{rolling}}(t) + P_{\text{aerodynamic}}(t),
$$

where $P_{\text{kinetic}}(t)$ is the power demand of the kinetic energy of the vehicle; $P_{\text{rolling}}(t)$ represents the power demand for overcoming ground resistance; and $P_{\text{aerodynamic}}(t)$ is the third component, which represents the power demand for overcoming the wind resistance. According to equation (2), the fuel usage for the kinetic energy of the vehicle can be calculated using the following formula:

$$
F_{\text{kinetic}} = \int_{t_1}^{t_2} (a \cdot v \cdot a)dt
$$

$$
= a \cdot a_1 \int_0^{t_1} v \cdot dt + a \cdot a_2 \int_{t_1}^{t_2} v \cdot dt + a \cdot a_3 \int_{t_2}^{t_3} v \cdot dt
$$

$$
= a \cdot a_1 (s_1 - s_2 + s_3)
$$

$$
= 0.
$$

According to equation (2), the fuel usage for overcoming ground resistance can be calculated using the following formula:

$$
F_{\text{rolling}} = \int_{t_1}^{t_2} (\beta \cdot v)dt
$$

$$
= \beta \int_{s_1}^{s_2} ds
$$

$$
= \beta s.
$$
According to equation (2), the fuel usage for overcoming wind resistance can be calculated using the following formula:

\[
F_{\text{aerodynamic}} = \int_{t_1}^{t_2} y \cdot v^3 \, dt \\
= y \int_{v_0}^{v_e} v^2 \, ds \\
= y \int_{v_0}^{v_e} (2 \cdot a \cdot s + V_e^2) \, ds.
\]

(8)

where \(v_0\) denotes the initial speed. In the process of uniform acceleration, in which the speed uniformly accelerates from \(V_e\) to \(V_e + \delta\), the fuel usage for this part is as follows:

\[
F_{\text{aerodynamic}_1} = y \int_{0}^{s_1} (2 \cdot a_1 \cdot s + V_e^2) \, ds \\
= y \int_{0}^{2V_e \delta / a} (2 \cdot a \cdot s + V_e^2) \, ds \\
= \frac{V_e^4}{4a} \left( 4V_e^2 \delta + 6V_e^2 \delta^2 + 4V_e^2 \delta^3 + \delta^4 \right).
\]

During the uniform deceleration process, the speed uniformly decelerates from \(V_e + \delta\) to \(V_e - \delta\). Similarly, the fuel usage for this part is as follows:

\[
F_{\text{aerodynamic}_2} = y \int_{0}^{2V_e \delta / a} [-2 \cdot a \cdot s + (V_e + \delta)^2] \, ds \\
= \frac{2V_e^4}{a} \left[ V_e^3 \delta + V_e \delta^2 \right].
\]

(10)

In the process of uniform acceleration, in which the speed uniformly accelerates from \(V_e - \delta\) to \(V_e\), the fuel usage for this part is as follows:

\[
F_{\text{aerodynamic}_3} = y \int_{0}^{s_2} [2 \cdot a_3 \cdot s + (V_e - \delta)^2] \, ds \\
= y \int_{0}^{2V_e \delta / a} [2 \cdot a \cdot s + (V_e - \delta)^2] \, ds \\
= \frac{V_e^4}{4a} \left[ 2V_e \delta - \delta^2 \right] (2V_e^2 + 2V_e \delta + \delta^2).
\]

(11)

Therefore, the total work done in one cycle is calculated as follows:

\[
F_{\text{aerodynamic}} = F_{\text{aerodynamic}_1} + F_{\text{aerodynamic}_2} + F_{\text{aerodynamic}_3} \\
= \frac{4V_e^4 \delta}{a} \left( V_e^2 + \delta^2 \right) \\
= y \delta (V_e^2 + \delta^2).
\]

Moreover, the total fuel usage in the OD is calculated as follows:

\[
Fuel = F_{\text{kinetic}} + F_{\text{rolling}} + F_{\text{aerodynamic}} \\
= yV_e^3 (V_e^2 + \delta^2) + \beta s.
\]

(13)

The amount of fuel consumed per unit of time cannot accurately represent the fuel consumption level of a vehicle. Instead, a better representation of the fuel consumption of a vehicle is the amount of fuel consumed through a unit distance. From equation (13), it can be seen that the fuel consumption (FC) per unit distance is as follows:

\[
FC = \frac{Fuel}{s} = y(V_e^2 + \delta^2) + \beta.
\]

(14)

From equation (14), it can be seen that the fuel consumption is proportional to the extent of the speed fluctuation (\(\delta^2\)) under the same mean speed (\(V_e\)). The greater the fluctuation, the greater the amount of fuel required to overcome the wind resistance, and the greater the probability of braking to ensure driving safety. Therefore, there will be more energy lost through friction as a greater amount of extra energy is converted into heat energy. The more the instances of braking, the more obvious the "stop-and-go" phenomenon while completing the same mileage. This is why frequent acceleration and deceleration incur greater fuel costs. As noted above, the variance of the triangular wave signal is half of the square of its amplitude, that is, \(\delta^2/2\). In other words, fuel consumption is proportional to the variance of the speed signal, and the fluctuation of the speed in subsequent experiments can be characterized by its variance.

3. Experiments and Discussion

The experimental verification included a simulation experiment and a field experiment that took advantage of real-time in-vehicle data, which were collected using an on-board diagnostic port reader installed in the experimental vehicle. This portable instrument has been used in previous studies [19]. Recording software was run in a laptop to capture the speed, instantaneous fuel consumption, engine speed, time traveled, current mileage, and other variables from the port reader. The temporal resolution of the data was 3 Hz. The simulation experiments were conducted using a moving average filter to generate driving cycles, with different speed variances from the real scenario. The field experiments were carried out with an autonomous vehicle under two driving modes: autonomous and human-driven.

3.1. Simulations Using Data from Real Scenarios. To verify the influence of speed variance on fuel consumption under real scenarios, we selected a route with diverse scenarios, including urban roads, expressways, and rural roads (see Figure 4). The test route is a 160 km round trip. Table 1
shows the basic information on the round trip. Trip 1 represents journey from the origin to the destination, and Trip 2 is the return trip.

The speed of the test cycle ranged from 0 km/h to 130 km/h. Driving behaviors include all possible behaviors such as acceleration, cruising, and deceleration. The cruising state occupies more than 50% of the operation time according to the statistical data in Table 1. As the speed fluctuation is caused by acceleration and deceleration, data visualization under these behaviors will help verify the relationship between speed fluctuation and fuel consumption. Figure 5(a) shows the vehicle fuel consumption (L/100 km) data at different speeds. At each speed point, we performed a simple calculation of the speed. Zhang et al. [20] classified driving behaviors based on the jerk (acceleration derivative) and analyzed the effects of various driving behaviors on fuel consumption. In this study, we calculated the difference between the current speed and the previous speed; based on this, a simple driving behavior was classified. If the difference is greater than 0 two consecutive times, it represents acceleration behavior. If the difference is less than 0 two consecutive times, it represents deceleration behavior. If the situation is neither of the two cases mentioned above, it represents the cruising speed. In Figure 5(a), the red dots represent acceleration, green dots represent cruising, and blue dots represent deceleration.

As shown in Figure 5(a), speed fluctuations have a significant impact on fuel consumption. When a vehicle is in deceleration mode, fuel consumption is very small. Throughout the trip, fuel is mainly consumed in the cruising and acceleration cycles. Fuel consumption during acceleration mode is higher than that during cruising mode. In order to illustrate the results more clearly, the fuel consumption of three modes (acceleration mode, cruising mode, and deceleration mode) at the same speed was averaged, as shown in Figure 5(b).

To further verify the relationship between fuel consumption and speed fluctuation, filters of different scales were applied to the original speed trace to generate driving cycles with different speed variances from the real scenario [21]. The filtering method uses a moving average filter. The syntax of the smoothing method is as follows:

(i) $yy = \text{smooth}(y, \text{smoothing\_point\_number})$, which smooths the data in column vector $y$ using a moving average filter. The results are then returned to column vector $yy$. The smoothing\_point\_number represents the span of the moving average. The data in column vector $y$ are the real and original scenario speed data, and the data in column vector $yy$ are the simulated speed data. Importantly, the span must be odd. For instance, if the span of the moving average is five, the first few elements of $yy$ are given as follows:

- $yy(1) = y(1)$
- $yy(2) = \frac{(y(1) + y(2) + y(3))}{3}$
- $yy(3) = \frac{(y(1) + y(2) + y(3) + y(4) + y(5))}{5}$
- $yy(4) = \frac{(y(2) + y(3) + y(4) + y(5) + y(6))}{5}$

Figure 6 shows the speed traces with different filter levels on Trip 1. The horizontal and vertical axes in Figure 6 present the sampling sequence and vehicle speed (km/h), respectively. The title of the first figure is the raw data, which refers to the real, original speed trace. The other eight figures show the speed traces with different filters whose moving averages are 19, 39, 59, 79, 99, 119, 139, and 159. As noted, the speed trajectory became smoother with the increase in the filtering level.

Figure 7 shows the trends of the speed variance and the mean value of the two cycles with smooth points, which indicates the scale of filtering. For both the departure and return drive cycles, the speed variance decreased almost linearly with the increase in the smoothing point number, while the mean velocity is almost the same as the values in Table 1.

Figure 8 shows the relationship between the fuel consumption (L/100 km) calculated by the VSP and speed variance, which indicates the magnitude of the speed fluctuation in the drive cycle. As noted, the fuel consumption increased almost linearly with speed variance in both the Trip 1 and Trip 2 drive cycles.

3.2. Field Experiments. To verify whether an autonomous vehicle can save fuel, field experiments were conducted on the fuel consumption of an autonomous vehicle (which could be toggled into the human-driving mode as needed) under two driving modes. This section describes the experimental settings, including the test track, test vehicle, and test speed.

3.2.1. Test Track. All experiments were conducted in a connected and automated vehicle test bed at the Weishui Campus of Chang’an University in Xi’an, China. The test bed has a 2.4 km circular track with four lanes, and a 1.1 km straight track with two lanes. The total area was approximately 282000 m² (approximately 58 acres). In these experiments, we collected data on the inner track, as indicated by the bold line in Figure 9.
Table 1: Basic information for the selected round trip.

<table>
<thead>
<tr>
<th>Sampling points</th>
<th>Avg. Speed (km/h)</th>
<th>Top speed (km/h)</th>
<th>Distance (km)</th>
<th>Fuel consumption (L)</th>
<th>Cruising time (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trip 1</td>
<td>16352</td>
<td>59.7</td>
<td>130</td>
<td>83.4</td>
<td>4.94</td>
</tr>
<tr>
<td>Trip 2</td>
<td>19271</td>
<td>48.8</td>
<td>123</td>
<td>80.3</td>
<td>5.0</td>
</tr>
</tbody>
</table>

Figure 5: Relationship between speed and fuel consumption.

Figure 6: Speed traces with different filters on route A.
3.2.2. Test Vehicle. As shown in Figure 10, an autonomous vehicle developed by the Chang’an University research team was used in the experiments. The test vehicle was a 2014 BYD SURUI that was retrofitted by modifying the steering, brake, throttle, gear shift, and power system into a drive-by-wire system controlled via controller area network (CAN) bus commands. After modification, the AV could be driven using computer commands and by human drivers. The test vehicle was equipped with a differential global positioning system (DGPS) receiver to collect the position and speed data. The model of the DGPS receiver was a BD982 manufactured by Trimble. The DGPS receiver records the instantaneous position data, that is, the latitude and longitude of the vehicle. The position accuracy of the DGPS receiver is within 10 cm. A Velodyne HDL-32e LiDAR was mounted on the roof of the AV. The LiDAR outputs 3D point cloud data of the surrounding environment within 80 m. The implementation of vehicle detection and tracking was based on the LiDAR data. One Balsar stereo camera was installed on both sides of the LiDAR, and one SICK millimeter wave radar was installed on both sides of the front of the vehicle. In addition, the AV was equipped with an industrial control computer (model ARK-3500), which had an i7 processor, 32 GB memory, 1 TB solid-state disk, 1050 Ti GPU, and a CAN bus interface card [22]. With such customization, the AV could be under both longitudinal and latitudinal control automatically for a complete route under normal conditions; thus, it can be classified as being at Level 3 automation. Nonetheless, this study focused only on longitudinal control. Therefore, as long as the longitudinal control was consistent, it was not sensitive to the automation level of the test AV.

3.2.3. Test Speed. We selected 20 km/h and 40 km/h as the test speeds. For each test speed, two driving modes were used. For the human-driven mode, the experiments were conducted three times with different speed fluctuations. In each experiment, the vehicle traveled several laps around the given track. Figures 11(a) and 11(b) show the speed and fuel consumption data collected from the autonomous and human-driven vehicles at speeds of 20 km/h and 40 km/h, respectively. In each figure, the curves in the first row represent the data from the autonomous mode, and those in the remaining three rows represent the data from the human-
Mean Speed: 19.4, Variance: 1.4

Mean Speed: 18.8, Variance: 4.0

Mean Speed: 19.0, Variance: 39.0

Mean Speed: 19.5, Variance: 15.7

Figure 11: Continued.
driven mode. For the human-driven mode, the experiments were carried out three times, the first of which was performed naturally, whereas the other two driving cycles were conducted with more speed fluctuations. The corresponding average speed, speed variance, distance, cumulative fuel consumption, and cumulative fuel consumption per 100 km were calculated and are listed in Table 2. The experimental results show that the fuel consumption (L/100 km) increased almost linearly with the increase in speed variance, as shown in Figure 12. Under the human-driven mode, the fuel consumption (L/100 km) increased by 5.6% and 14.7% at 20 km/h and 40 km/h, respectively, compared with that of the autonomous mode. In this study, aggressive behaviors are defined as cycles with similar average speeds but higher speed variances. As shown in the last sub-figure in Figures 11(a) and 11(b), fuel consumption increased by approximately 60% under more aggressive driving behaviors, compared with that of autonomous driving.

3.3. Discussion. Previous studies have focused on optimizing the driving behavior by providing drivers with recommended speed or designing the trajectory planning and tracking algorithms for autonomous vehicles to achieve energy-efficient goals. The result of this study that the fuel consumption increases linearly with the increase in speed fluctuation under the same mean speed provides a solid theoretical basis for previous researches. Because autonomous vehicles are controlled by electronic and mechanical devices, their speed can be stabilized at the desired level with small errors through intelligent sensing, motion planning, and motion control methods. We can reduce the speed fluctuation to the maximum possible extent to achieve lower fuel consumption under safe conditions. For example, for future smart vehicles, the speed variance can be regarded as the control target of the vehicle ECU, and the most economical energy-saving strategy can be achieved by automatically controlling the amount of fuel injected into the engine. In this way, the fluctuation of the speed will be kept within a small range.

Furthermore, in the era of intelligent connected vehicles, vehicle speed can be automatically controlled according to the information sent by the roadside unit, and other vehicles, to achieve minimum speed fluctuation. For example, when a connected vehicle passes a traffic intersection, an optimized trajectory can be planned in advance, and motion control technologies can be used to accurately control the vehicle for eco-driving purposes. If there is a group of vehicles in the region, the speed variance of all vehicles in the region can be considered as the control objective to be achieved in the global goal of saving energy and reducing emissions.
In this study, speed variance was used to represent the magnitude of speed fluctuation. Furthermore, the relationship between fuel consumption and speed fluctuation was studied. To verify the validity and correctness of the relationship, simulations were performed using data from a real scenario, and fuel consumption tests were performed for a human-driven vehicle under different speed conditions. To further verify whether autonomous vehicles can save energy, fuel consumption experiments in both human-driven and autonomous modes were conducted and compared. Based on the simulation analysis and field experiments, the following conclusions were obtained:

(1) Speed fluctuation is caused by acceleration and deceleration. When a vehicle is in deceleration mode, fuel consumption is very small. Throughout the trip, fuel is mainly consumed in the cruising and acceleration cycles, but the fuel consumption in the acceleration mode was much higher than that in the cruising mode.

(2) Fuel consumption increases monotonically with respect to the speed variance. The results from both the simulation and field experiments show that fuel consumption increases almost linearly with the increase in speed variance. Theoretically, the speed control performance of autonomous vehicles is superior to that of human-driven vehicles. The experimental data showed that, in the human-driven mode, fuel consumption was 5.6% and 14.7% more at 20 km/h and 40 km/h, respectively, compared with that of autonomous driving. Moreover, fuel consumption increased by nearly 60% under aggressive human-driving behavior.

(3) From the viewpoint of being energy-saving, the effective chemical energy of fuel combustion is converted into three parts: the kinetic energy of the vehicle, the power used to overcome the rolling resistance, and the wind resistance. For a vehicle, frequent braking and acceleration will increase the "stop-and-go" incidences throughout the running time, resulting in greater fuel consumption for the trips of the same distance. In the soon-to-come era of connected and automated vehicles, V2I and vehicle-to-vehicle (V2V) communications can be used to reduce the possibility of this "stop-and-go" phenomenon, along with fuel consumption reductions.

**Data Availability**

The data used to support the findings of this study have not been made available because these data still need to be used in other unfinished studies.

**Conflicts of Interest**

The authors declare that they have no conflicts of interest.

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