Energy efficiency of autonomous vehicles on hilly roads

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Abstract. Energy efficiency is traditionally among the main development trends in the automobile industry. We suspected that intelligent speed control systems can provide economic and ecological benefits for implementing civil autonomous driving technologies. We introduced the approach for autonomous driving, which is based on the analysis of the precise Digital Terrain Model (DTM) and optimal vehicle control actions with respect to a requested transport task, which can be a task of fuel or energy economy in this particular case. We addressed the research question of fuel economy estimation with respect to the reference parameter that is applicable to compare different control algorithms. We demonstrated the use of roadway-related factors of DTM to affect fuel consumption. We contributed the algorithm for saving fuel while driving on a hilly road and examined the influence of vehicle load on possible economy values. We compared fuel and energy-saving values of gasoline and electric vehicles based on the same chassis with and without use of the proposed algorithm. Practical results of tests on public roads are presented.

1. Introduction

This study focuses on predicting the possible economic and ecological benefits of intelligent speed control systems of autonomous road vehicles. Thus, it is also concerned with the subject of autonomous driving system design and the subject of fuel (energy) economy.

The rest of the article is organized as described below.

In Section 2, we provide a description of state-of-the-art research in the field of autonomous driving design and in the field of fuel consumption analysis and optimisation.

In Section 3, we introduce an approach for fuel (energy) saving on hilly roads, describe the way in which we estimate possible economy values, and describe the process of mathematical model verification and validation.

Section 4 describes experimental research of real vehicles on public roads and represents results of fuel and energy-saving values for gasoline and electric vehicles based on the same chassis with and without use of the proposed algorithm of intelligent speed adjustment. An analysis of the vehicle’s load influence on possible economy values is also presented.

The main results and novel contributions are highlighted in the conclusion.

2. State-of-the-art Research

Development of autonomous vehicle technologies has been ongoing in the air, marine [1, 2], ground, and space domains for a long time in different ways and with different results. We focused our attention
on the ground domain only. Automation of road vehicles has been driven by approximately a century of research in different countries [3]. Several scientific studies [4-6] have addressed the issues of automatic vehicle control, such as the object component base, the mathematical apparatus and its implementation, and technical vision systems.

Developmental projects on autonomous vehicle technologies in the ground domain are currently being undertaken by all global motor manufacturers, especially those in the US, Germany, Japan, and China. Automobile groups such as Ford, Daimler, Volkswagen, Toyota, Honda, GM, Geely, Tata, and Tesla, as well as other major technological organisations such as Google, Continental, Delphi, Siemens, and Bosch are also involved in these projects. Other players in the field include defence departments and agencies of different countries, universities (e.g., Stanford University, Carnegie Mellon University, Technical University of Munich, University of Karlsruhe, Fraunhofer Institute, University of Minnesota, Universidad Politécnica de Madrid [7]), and many other institutions. Thus, autonomous driving is a global trend and no automakers, suppliers, or technological companies will be able to overlook it [8-11].

We suppose that one of the main reasons why autonomous driving technologies have not yet been widely deployed for everyday life use is that car manufacturers and technological companies have chosen the paradigm of variability of manoeuvres and driving modes at the tactical level of vehicle control. This paradigm makes autonomous vehicles essentially sensitive to the quality of the technical vision and decision-making systems. These systems are typically based on artificial intelligence solutions, and thus, achievement of 100% reliability seems ambiguous [12].

We suggest decreasing the number of degrees of freedom at the tactical level of vehicle control [13, 14] and excluding the variability of manoeuvres, while retaining the variability of driving modes. We offer a simplified approach for autonomous driving and a more reliable and less expensive solution. This approach can be compared with a virtual spatial railway for the vehicle, which acts like a train. Accordingly, in the simplest case, the vehicle should decrease its driving velocity and stop when it detects an obstacle or risk of any type.

Optimisation of a vehicle’s fuel consumption is a complex subject, and numerous variables influence vehicle energy and emission rates. These variables can be classified into six broad categories [15]: travel-related, weather-related, vehicle-related, traffic-related, driver-related, and roadway-related factors.

Travel-related factors represent eco-routing systems, which are capable of providing the shortest-distance route and the shortest-duration route, and routes that minimise fuel consumption with respect to traffic conditions. The possible fuel economy improvements of eco-routing systems achieve values in the range from 8.73% to 42.15% [15].

Weather-related factors deal with parameters of ambient temperature, humidity, and wind effects. These factors affect fuel consumption through vehicle attachments, e.g., the air conditioner and the water pump. According to the U.S. Environmental Protection Agency, fuel economy improvements in this case can achieve values of up to 1%.

Vehicle-related factors belong to the core factors that influence fuel economy (e.g. engine size and type, its characteristics, loading, and aerodynamics). The fuel saving efficiency can reach any value, and it depends only on what type of vehicle and scenario will be used as a basis for comparison.

Traffic-related factors include traffic flow and traffic signalling. Several studies have indicated that the use of traffic signal information has significant potential to save fuel. Fuel consumption can be reduced by 22–50% depending on the application scenario considered [15].

Driver-related factors refer to driver behaviour and aggressiveness, which are typically identified by speed and acceleration profiles. Several studies have indicated that aggressive driving can cause 30–40% higher fuel consumption compared to calm driving [16].

Roadway-related factors refer to the physical characteristics of a road (roadway grade, roughness, curvature). In this case, an eco-driving system was based on model predictive control (MPC) to run a vehicle on roads with up and down slopes [17]; their simulation on a virtual road indicated fuel savings in the range of 5–7.04% when the eco-driving vehicle was compared with automatic speed control drive vehicle. This result was achieved by increasing the vehicle speed before entering the uphill slope and
taking advantage of the down-hill slope. In another paper, the method of global and local optimisation was used [18], and a fuel reduction of 5.5% was obtained using simulation techniques. Researchers have also appraised the available efficiency of these systems as being in the range of 3–20% for fuel savings, according to [15], and up to 6.89–24.78%, according to [19]. The existing on-the-market Volvo “I-see” system is known, and it has reported fuel savings of about 5%, but it is not clear how this value can be confirmed.

We work with a precise Digital Terrain Model, so we will further discuss only roadway-related factors in this paper. The value of the fuel savings is critically affected by the value of fuel consumption that is used as a reference value for comparison. For example, a decrease in the average velocity on a route will lead to a reduction of air and rolling resistance factors and lead to fuel savings, but it will also increase the trip time. The next question is associated with the problem of conducting a road test on a long route because it is influenced by traffic and environmental conditions and it is difficult to repeat. Thus, we addressed the research question of estimating fuel economy with respect to the reference parameters that are required to compare different control algorithms and conduct a real road test on a long route.

3. Approach for Fuel (Energy) Saving on Hilly Roads

Fuel consumption of the road vehicle with a gasoline engine can be estimated using the following equation [20]:

$$B_{IC} = \frac{\int b_c \left[ \left( m f g \cos \alpha + \frac{1}{2} c_w A v^2 \right) + m (a + g \sin \alpha) + B_r \right] u \, dt}{\int u \, dt},$$

where $B_{IC}$ is the fuel consumption per distance, $b_c$ is the specific fuel consumption, $\eta$ is the average transmission efficiency, $m$ is the vehicle mass, $f$ is the average rolling resistance, $g$ is the acceleration of gravity, $\alpha$ is the longitudinal road inclination, $\rho$ is the density of air, $c_w$ is the coefficient of aerodynamic drag, $A$ is the front vehicle area, $v$ is the vehicle velocity, $a$ is the vehicle longitudinal acceleration, $B_r$ is the braking resistance, and $t$ is time.

We consider comparing the fuel consumption of different driving modes with respect to the same driving time during all the tests. First, we set the nominal value for the driving velocity and lower and upper limits for speed regulation. Then, we analysed data from the Digital Terrain Model and estimated the function of longitudinal road inclination angles compared to the distance driven. We then estimated the optimal speed profile for the current route. We then estimated the fuel consumption and driving time with activated intelligent speed adjustment, determined the average velocity, and estimated the referenced fuel consumption with this constant speed. Thus, the reference parameter that is applicable to the fuel consumption comparison using different control algorithms is the driving time.

The energy consumption of electric vehicle is specified as an integration of the output power of the electric vehicle at the battery terminal. The total power flows at the battery terminal can be defined as [21, 22]:

$$P_{total} = P_{bat_{out}} - P_{bat_{in}} = P_{bat_{active}} + P_{bat_{aux}} - P_{bat_{in}},$$

If we simplify the above equation and make assumptions about braking, regenerative braking, and auxiliary load absence, it will lead to the following equation:

$$B_{EV} = \frac{\int \eta_t \eta_m \left[ \left( m f g \cos \alpha + \frac{1}{2} c_w A v^2 \right) + m (a + g \sin \alpha) + B_r \right] u \, dt}{\int u \, dt},$$

where $B_{EV}$ is the energy consumption per distance, $\eta_t$ is the average transmission efficiency, and $\eta_m$ represents motor drive efficiency.

In the next stage, we need to find a way to verify the unknown parameters from equations (1) and (3). We suggest performing road tests on public roads using a predetermined DTM. This step will provide an advantage for the fuel consumption model validation in further simulations of fuel consumption on a long route with a known DTM.
4. Setup and Implementation

The fuel consumption experiment was performed on a highway between Moscow and Volokolamsk using a gasoline Chevrolet Cruze (experimental autonomous road vehicle). Figure 1 illustrates the altitudes of the highway compared to the travelled distance. The test road distance was 99.8 km, and the altitudes were obtained from a DTM with a height accuracy of 10 cm. The maximum difference in the altitude on the route was 163.3 m. To obtain a clear understanding of the fuel economy values, we estimated both driving directions: forward and then backward.

The unknown fuel consumption model parameters were determined by optimisation through comparison of the simulation results with those of road tests on the part of the test road that is identified with the red colour in Figure 1, for a total distance of 32 km while driving in both directions.

The specific fuel consumption \( b_g \) and the fuel consumption map of the experimental vehicle were obtained from the CAN bus (Controller Area Network [23,24]) by analysing OBD-II PIDs data [25] with the OBDLink MX device [26]; this is an imprecise method, but we consider it to be cost-effective and applicable for evaluation and rapid prototyping purposes. The adjusted parameters are as follows: \( b_g=7.9292\times10^{-5} \text{ g/(W}\cdot\text{s}) \); \( \eta=0.95 \); \( m=1500 \text{ kg} \); \( f=0.01 \); \( g=9.81 \text{ m/s}^2 \); \( \rho=1.22625 \text{ kg/m}^3 \); and \( c_w=0.3 \); \( A=2.3768 \text{ m}^2 \). The model adequacy was examined by comparing the results of road tests with those of simulations, and further statistical analysis of the error functions. Figure 2 shows the comparison between experimental and simulation data. The relative error of the estimated fuel trip consumption was within 2.8%.

Figure 1. Federal highway altitudes (Moscow to Volokolamsk).

Figure 2. Fuel consumption model validation.
After validation of the fuel consumption model, we simulated driving on a whole route in both directions. The following assumptions were made: we simulated driving at the highest gear in the transmission (rates were detected by analysing the OBD-II PIDs data) and assumed that the gearbox torque converter is blocked. We did not use braking, there was no external wind load, and we neglected the manoeuvring effect. Furthermore, the road’s and wheels’ adhesion properties were unchanged, there were no other traffic participants, and weather conditions (temperature, humidity, pressure) were not taken into consideration. Such a scenario is not realistic, but we tried to show the possible values of fuel economy under ideal conditions, the proposed comparison method, and the practical use of precise geoinformational data.

Figure 3 illustrates the intelligent speed control regulation during the simulation process, according to the proposed algorithm.

![Figure 3. Intelligent speed control regulation.](image)

The main results of the simulations are shown in Table 1. In both driving directions on the entire route, we compared two driving modes: 1) driving with intelligent speed control with a speed regulation algorithm at a nominal value of 95 ±15 km/h, depending on whether the route has an upward or downward slope; and 2) driving with a constant velocity as the average velocity in the first case (and therefore the same time of driving). Simulations of the fuel consumption were also performed for the case of a variable vehicle mass.

Table 1. Simulation results for gasoline vehicle fuel consumption while driving on a hilly road with and without intelligent speed control.

| Veh. mass, kg | Forward direction (100 km) | Inverse direction (100 km) | Both ways (200 km) |
|--------------|---------------------------|-----------------------------|-------------------|
|              | Const.V km/h | 80 to 110 km/h | Econ., % | Const.V km/h | 80 to 110 km/h | Econ., % | Const.V km/h | 80 to 110 km/h | Econ., % |
| Fuel cons., l | 4.61 | 4.51 | −2.30 | 4.41 | 4.32 | −2.02 | 9.02 | 8.82 | −2.16 |
|              | 4.76 | 4.63 | −2.76 | 4.54 | 4.42 | −2.58 | 9.30 | 9.05 | −2.67 |
|              | 4.91 | 4.75 | −3.21 | 4.67 | 4.53 | −3.13 | 9.58 | 9.27 | −3.17 |
|              | 5.05 | 4.87 | −3.65 | 4.81 | 4.63 | −3.64 | 9.86 | 9.50 | −3.64 |
|              | 5.20 | 4.99 | −4.08 | 4.94 | 4.74 | −4.12 | 10.14 | 9.73 | −4.10 |

An increase of the vehicle mass resulted in an increase of fuel economy for the intelligent speed control system. An increase in the driving velocity up to 150 km/h for the experimental car eliminates...
the efficiency of the proposed control algorithm. The optimisation of fuel consumption for autonomous
driving mode on a hilly test road over a distance of 200 km resulted in up to 4.1% savings compared
with constant-speed driving for the same time.

In the next stage, the experimental vehicle was replaced with an equivalent electric vehicle [27]. The
motor drive efficiency was considered to be equal to 0.9 [28].

The main simulation results are shown in Table 2. The optimisation of energy consumption resulted
in up to 2.4% savings compared with constant-speed driving with for same time using the full vehicle
mass.

Table 2. Simulation results for electric vehicle energy consumption while driving on a hilly road
with and without intelligent speed control.

| Veh. mass, kg | Forward direction (100 km) | Inverse direction (100 km) | Both ways (200 km) |
|--------------|---------------------------|---------------------------|-------------------|
|              | Const.V 80 to 110 km/h    | Econ., Energy, kWh        |                    |
|              | km/h     | Energy, kWh               | Energy, kWh       | Energy, kWh       | Energy, kWh       | Energy, kWh       | Econ., % |
| 1400         | 13.28    | 13.13 −1.06               | 12.63 12.58 −0.37 | 25.91 25.70 −0.72 |
| 1500         | 13.68    | 13.48 −1.45               | 12.99 12.88 −0.84 | 26.68 26.37 −1.15 |
| 1600         | 14.09    | 13.84 −1.83               | 13.36 13.19 −1.30 | 27.45 27.02 −1.57 |
| 1700         | 14.51    | 14.19 −2.21               | 13.73 13.49 −1.77 | 28.24 27.68 −1.99 |
| 1800         | 14.93    | 14.54 −2.58               | 14.11 13.79 −2.23 | 29.03 28.33 −2.41 |

Figure 4 illustrates the possible economy values compared to the vehicle’s load, which shows linear
dependence.

A road vehicle with an inner combustion engine demonstrated higher fuel saving values on a hilly
road using intelligent speed adjustment compared with a similar electric vehicle.

5. Discussion and Conclusions

Estimating the fuel or energy consumption is not easy because there are many influencing parameters.
Some papers on this subject showed values of savings for some routes without analysing the driving
modes. We tried to compare fuel consumption of different driving modes and control algorithms with
respect to the same driving time during all tests. We have demonstrated the practical use of the Digital
Terrain Model in the task of autonomous driving and fuel consumption optimisation on hilly roads.
An approach for fuel (energy) saving on hilly roads, the process of mathematical model verification and validation, an experimental research method of testing the real vehicle on public road, and analysis of the vehicle’s load influence on possible economy values have been introduced.

In addition, we have shown the possible values of fuel consumption (energy) savings for a gasoline and electric passenger car under ideal conditions. Fuel consumption optimisation for autonomous driving mode on a hilly test road over a distance of 200 km resulted in up to 4.1% savings for the experimental vehicle and up to 2.4% for an equivalent electric vehicle.

It is essential to solve the issues surrounding optimal vehicle control using the precise geoinformation environment.

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