DOI: https://doi.org/10.46354/i3m.2019.mas.006

FUEL-OPTIMAL PATH FINDING ALGORITHM USING TRAFFIC INFORMATION AT URBAN INTERSECTION

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ABSTRACT
Intelligent Transportation System (ITS) is actively studied as the sensor and communication technology in the vehicle develops. The Intelligent Transportation System collects, processes, and provides information on the location, speed, and acceleration of the vehicles in the intersection. This paper proposes a fuel optimal route decision algorithm. The algorithm estimates traffic condition using information of vehicles acquired from several ITS intersections and determines the route that minimizes fuel consumption by reflecting the estimated traffic condition. Simplified fuel consumption models and road information (speed limit, average speed, etc.) are used to estimate the amount of fuel consumed when passing through the road. Dynamic Programming (DP) is used to determine the route that fuel consumption can be minimized. This algorithm has been verified in an intersection traffic model that reflects the actual traffic environment (Korea Daegu Technopolis) and the corresponding traffic model is modeled using AIMSUN.

Keywords: Fuel Consumption, Traffic Information, Dynamic Programming(DP), Intelligent Transportation Systems(ITS), Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks (AIMSUN)

1. INTRODUCTION

As the consumption of fossil fuels increases worldwide, environmental pollution becomes a more serious problem. The engine of an automobile burns fuel and exhaust many kinds of harmful gas. Typical automobile exhaust gas contains hydrocarbons (HC), nitrogen oxides (NOx), carbon monoxide (CO), carbon dioxide (CO2), and particle mass (PM). Automobile exhaust pollution has a detrimental effect on the human body and cause environmental changes such as global warming. Automobile emissions regulations are being strengthened to solve environmental problems caused by engine exhaust gas. Various technologies have been developed to improve fuel efficiency and satisfy environmental regulations. Engine control technologies such as 'lean-burn' and 'engine downsizing' have greatly increased engine efficiency, and component processing technology has significantly reduced power transmission losses. Eco-friendly vehicles using two or more distinct types of power (Fuel Cell Electric Vehicle, (Plug-in) Hybrid Electric Vehicle, etc.) are being actively developed and driving on the road.

However, not only the automotive manufacturing / control technology but also the actual driving environment experienced by the driver is highly related to fuel economy and exhaust pollution. (Min Zhou 2016) The actual driving environment includes the driving behavior of the driver, the traffic environment (queue length, speed limit, etc.), and the road environment (weather, traffic light, road curvature, etc.). Road information and traffic information are required to control the vehicle in accordance with the actual driving environment. The ITS has various measuring equipments (camera, radar, etc.) and communication systems (WAVE, 5G, etc.), so it can provide information such as traffic average speed and traffic signal schedule to the vehicles. There are many studies on how to reflect this information in the vehicle speed control algorithm and routing algorithm. (Hesham Rakha 2011; Matthew Barth 2011; Hao Yang 2016; Raj kishore Kamalanathsharma 2014; M.A.S. Kamal 2010; Matej 2016; Jie Sun 2015; Xian Huang 2018) These algorithms are very helpful in preventing traffic accidents and improving fuel economy.

In this paper, we propose an algorithm to determine the route that can improve fuel economy by using road / traffic information delivered from ITS. First, the traffic flow model is used to estimate the state of traffic such as the average speed and the average travel time for each road. Second, simplified fuel consumption model is used to estimate instantaneous fuel consumption at vehicle speed and acceleration. The estimated instantaneous fuel consumption and road information are used to determine the amount of fuel consumed to pass the road. Instantaneous fuel consumption refers to the amount of fuel consumed in a steady state, ignoring the transient state of the engine. It is assumed that the transient state of the engine is negligible because it is very small compared to the normal operating state. Third, the algorithm defines a cost function to minimize the amount of fuel consumed to pass the road and derives the optimal path using Dynamic Programming (DP). The DP algorithm is an algorithm for finding a globally optimal solution when the status of the entire system is known. The algorithm was programmed using Python and validated at the intersection AIMSUN traffic model reflecting the actual traffic environment (Korea Daegu Technopolis). AIMSUN is a software that can microscope the traffic environment and verify vehicle behavior in traffic flow.

2. TRAFFIC STATE ESTIMATION MODEL

The traffic state estimation model estimates the 'Travel Time' and 'Travel Fuel Consumption'. The traffic state estimation model uses average speed and traffic density based on Green-shield linear traffic model. The Green-shield linear traffic model assumes that the traffic average speed and traffic density have a linear relationship. The relationship can be seen in Figure 1.

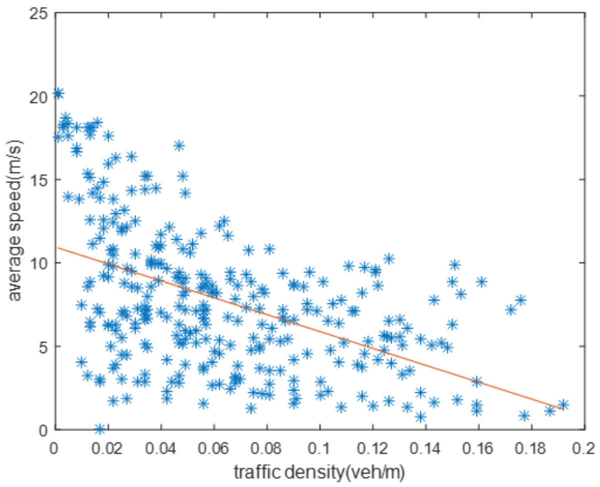

Figure 1: The relationship between space mean velocity and traffic density

2.1. Travel Time

The 'Travel Time' means the time required to pass through each road. Travel time(T_{Travel}) can be estimated using 'space mean speed(V_{space_mean})', 'speed limit($V_{\lim it}$)' and 'road length(L_{road})'. The equations for the travel time are (1).

$$T_{Travel} = \max\left(\frac{L_{road}}{V_{space\_mean}}, V_{\lim it}\right) \quad (1)$$

Space mean speed is closely related to fuel consumption. The relationship can be seen in Figure 2. It can be seen that the fuel consumption according to the average speed increases in a specific section. This means that the engine efficiency in not good in the corresponding speed section. Even if fuel consumption is minimized, excessive travel time is not a reasonable solution. Therefore, travel time can be applied as a constraint on the cost function.

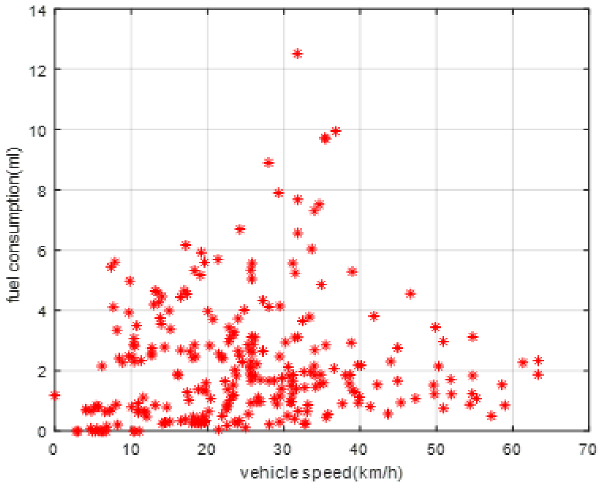

Figure 2: The relationship between space mean velocity and fuel consumption

2.2. Travel Fuel Consumption

The 'Travel Fuel Consumption' means the fuel consumption required to pass through each road. Travel fuel consumption(FC_{travel}) can be estimated using 'instantaneous fuel consumption rate(FR_{inst})' and 'travel time(T_{travel})'. The equations for the travel time are (2).

$$FC_{travel} = FR_{inst} \times T_{travel} \quad (2)$$

The instantaneous fuel consumption rate is the fuel consumption rate, which is determined only by the current state, assuming a steady state, and is determined by the longitudinal vehicle dynamics and the simplified fuel consumption rate model. The instantaneous fuel consumption rate is calculated by the simplified fuel consumption rate model. (Engin Ozatay 2013; Hesham Rakha 2011) Actual engines have nonlinear fuel consumption characteristics. It appears to be an overly complex formula and requires a long computation time. Simplified fuel consumption rate model cannot calculate accurate fuel consumption, but they can represent fuel consumption trends and have simple formulas and short computing times. As a result, a simplified fuel consumption rate model can be used to find the trends to minimize fuel consumption. The equations for the constructed model are (3).

$$FR_{inst} = \frac{m}{eH_L \eta_{drive}} \times a_{input}(t) \times v(t) + \frac{P_{Loss} \times V_d}{4\pi \times eH_L}\left(\frac{\gamma(t)}{R_{wh}}\right) \times v(t) + \dot{m}_{idle} \quad (3)$$

The fuel consumption model is related to longitudinal vehicle dynamics. The longitudinal vehicle dynamics can be seen in Figure 3 and the equation is (4) - (6). Table 1 shows the vehicle parameter.

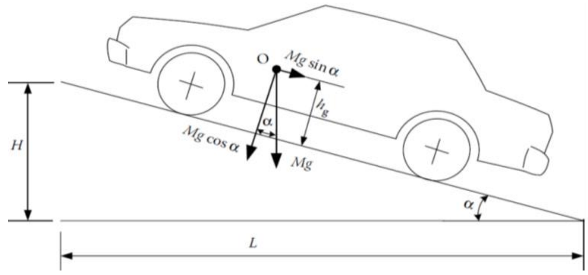

Figure 3: Longitudinal Vehicle Dynamics

$$M\frac{dv(t)}{dt} = F_{tract}(t) - F_{aero}(t) - F_{grade}(t) \quad (4)$$

$$F_{aero} = \frac{1}{2}\cdot\rho\cdot A_f\cdot C_d\cdot v^2(t) \quad (5)$$

$$F_{grade} = M\cdot g\cdot \sin(\alpha) \quad (6)$$

Table 1: Vehicle Dynamics Parameters

Vehicle Mass - M $[kg]$	1202
Frontal Area - A_f $[m^2]$	2.7
Air Drag Coefficient - C_d $[-]$	0.3
Air Density - ρ $[kg/m^3]$	1.206

A longitudinal vehicle dynamics model and a simplified fuel consumption model were verified using Carsim. Carsim is software that is primarily used to simulate the dynamic behavior of a vehicle. The verification result is the same as Figure 4 and Figure 5. In the graph, the blue line represents the nonlinear model and the red line represents the simplified model. The tendency of the simplified fuel consumption rate model is the same as the tendency of the non-linear fuel consumption rate model.

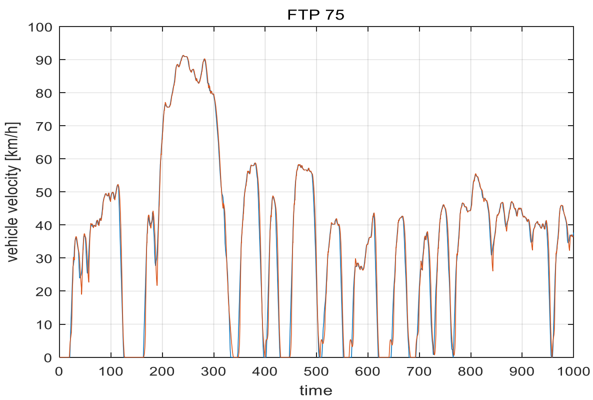

Figure 4: Vehicle velocity estimation result for FTP-75 city cycle

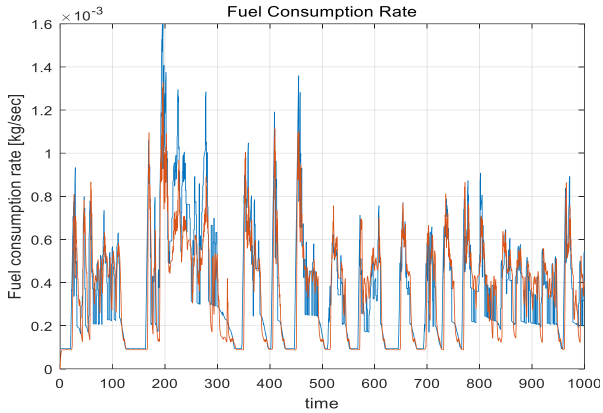

Figure 5: Instantaneous fuel consumption estimation result for FTP-75 city cycle

3. FUEL-OPTIMAL PATH FINDING ALGORITHM

The Fuel optimal routing algorithm uses dynamic programming to derive a path that minimizes fuel consumption.

3.1. Dynamic Programming

Dynamic programming, designed by Richard Bellman, is an analysis technique used to find global optimization solutions for complex systems. Dynamic programming divides a complex optimization problem into several simple sub-problems and derives the optimal solution of the complex problem by solving the sub-problems. In order to apply dynamic programming, a value function is designed for the purpose.

3.2. Cost Function

This algorithm aims at minimizing fuel consumption and reaching the destination. Depending on the purpose, the cost function($Cost\_function$) is designed to minimize fuel consumption(FC_{travel}). That is, the path that can minimize the total fuel consumption from the departure time(T_0) to the arrival time(T_f) at the destination is determined. The formula for the cost function is (7).

$$Cost\_function = \int_{t_o}^{t_f} FC_{travel}\, dt \quad (7)$$

The weighted graph of the road is determined by the cost function and is shown in Figure 6. The weight graph consists of nodes and sections, nodes represent intersections, and sections represent roads. Weights are assigned to each section. Each node is assigned an ID corresponding to an intersection.

Unlike other path finding algorithms that minimize travel time or travel distance, the route is determined by comparing the fuel consumption of the entire route.


Figure 6: Weighted graph for actual intersections

4. SIMULATION & RESULT

4.1. Simulation Environment

The Fuel - optimal path finding algorithm is implemented using Python. The algorithm was verified by an intersection traffic model reflecting the actual urban traffic environment. The intersection traffic model was designed using AIMSUN. AIMSUN is a microscopic traffic simulation software, which can simulate traffic flow through the movement of individual vehicles. AIMSUN worked with Python 2.7.13 to control the vehicles in the intersection traffic model.

The modeling target is 19 intersections located in Technopolis, Daegu, Korea. In order to simulate actual traffic environment, road characteristics (traffic signal schedule, road shape) and traffic characteristics were reflected in urban intersection traffic model. The urban intersection traffic model is the same as Figure 7. The traffic signal schedule configuration is shown in Figure 8. Figure 9 shows the traffic simulation screen using AIMSUN.

To verify this algorithm, we compare the simulation result with the shortest path finding algorithm to minimize travel distance. The performance of the algorithm was verified by comparing fuel consumption.

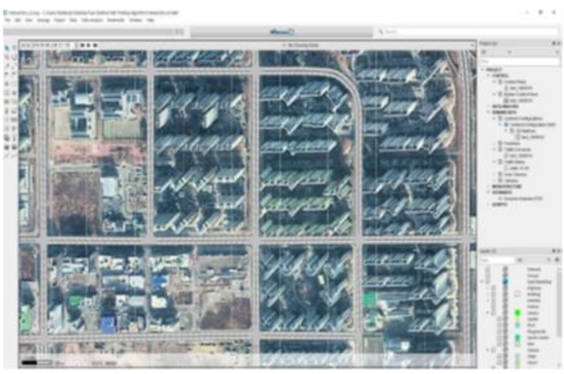
Figure 7: AIMSUN urban intersection traffic model

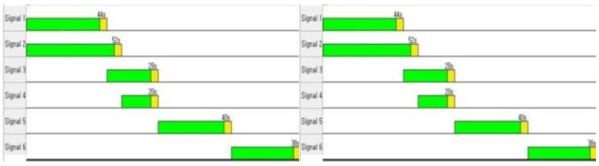
Figure 8: AIMSUN traffic model - traffic signal schedule

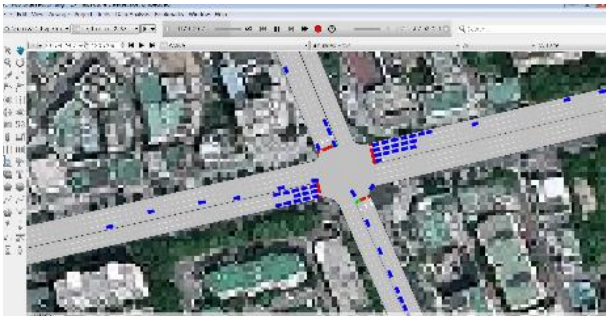
Figure 9: AIMSUN Traffic simulation screen

4.2. Simulation Result

The simulation results are shown in Figure 10. 200 vehicles of the total 4000 vehicles were controlled. The verification vehicle starts from node 24 and arrives at node 3. We simulated the saturation traffic situation of commuting time.

The red path represents the shortest path and the yellow represents the Fuel-optimal path finding algorithm. Table 2 shows the simulation result. The shortest path finding algorithm consumes 74 liters of fuel with an average travel time of 2148 seconds and the fuel-optimal routing algorithm consumes 68 liters of fuel with an average delay of 2250 seconds. As a result, it was confirmed that the fuel-optimal path finding algorithm improved the fuel efficiency of the controlled vehicle by approximately 9.04%. Although the fuel-optimal path finding algorithm has a longer travel time, it can be seen that the fuel consumption is lower.


Figure 10: Simulation results - path comparison

Table 2: Simulation results

Shortest path finding algorithm	
Fuel Consumption	74.86 [L]
Average Travel Time	2148.0 [sec]
Fuel-optimal path finding algorithm	
Fuel Consumption	68.09 [L]
Average Travel Time	2250.4 [sec]

5. CONCLUSION

In this paper, we propose an algorithm to find the path that minimizes fuel consumption. The algorithm uses traffic information and vehicle information. The average travel time is estimated using traffic information. The instantaneous fuel rate is calculated using simplified fuel consumption model and vehicle status. The instantaneous fuel rate and average travel time are used to calculate travel fuel consumption, which is the amount of fuel consumed in passing through the road. The cost function is designed using the travel fuel consumption and the weight of each road is given. Dynamic Programming is used to find a path that minimizes the corresponding cost function over the entire travel period. To verify the algorithm, we modeled intersection traffic model for 19 actual traffic environment of 19 actual intersections of Daegu Technopolis, Seoul, Korea. Micro traffic simulation software AIMSUN was used as a traffic modeling environment. A total of 4,000 cars were used to construct traffic, of which 200 vehicles controlled the route. We compared the fuel consumption of the vehicles with the shortest path finding algorithm and the fuel optimal path finding algorithm respectively. It was confirmed that the fuel-optimal path finding algorithm uses 9% less fuel and 100 seconds longer travel time. It can be seen from this result that reducing the travel time or travel distance is not the only wat to reduce fuel consumption.

ACKNOWLEDGMENTS

This work is supported by Institute for Information & communications Technology Promotion(IITP) grant funded by the Korea government(MSIP) (No. R7117-16-0132, The development of future technology for mixed traffic intersection integrated environmental information regarding the autonomous at the crossroads of the city)

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