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Energy-Saving Effect of Longitudinal Control Algorithm based on Traffic State of Electric Vehicles

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Abstract

This study reports the evaluation of the energy-saving effect of a longitudinal control algorithm based on the traffic states of electric vehicles. For realizing energy saving, the control structure should observe the various traffic states and reduce wasteful acceleration and deceleration. The longitudinal control for energy-saving proposed in this paper is realized using a velocity pattern generation algorithm and a velocity control algorithm. This paper proposes a longitudinal control algorithm to save energy in electric vehicles driven alongside ordinary vehicles on a street and evaluates the energy-saving effect of the control.

Keywords: electronics and control, autonomous driving system, intelligent transport system (ITS), energy-saving ITS

1 Introduction

This paper reports an evaluation of the energy-saving effect of a longitudinal control algorithm based on the traffic states of electric vehicles.
Recently, there has been an increase in research on energy-saving technologies owing to rising oil prices and an increase in eco-consciousness. In the automotive field, research has been carried out on energy-efficient technologies for several years not only to improve engine efficiency and reduce air and travel resistance and weight saving but also to develop new approaches based on the intelligent transport system (ITS) technology [1]-[3]. In fact, the development of a system of heavy-duty vehicles aiming at energy saving was started in Japan under NEDO's Development of Energy-saving ITS Technologies project in 2008.
This study is a part of the Energy-saving ITS Technologies project and aims at the development of a longitudinal control algorithm to save energy in electric vehicles driven alongside ordinary vehicles on a street. The proposed longitudinal control algorithm for energy saving is predictably effective for not only internal combustion engine vehicles but also electric vehicles. This study adopts the longitudinal control algorithm to save energy in electric vehicles and evaluates the effect of the control.
The following sections explain the proposed longitudinal control algorithm used to save energy in electric vehicles and describe the evaluation of the proposed longitudinal control algorithm for light electric vehicles.

2 Longitudinal Control Algorithm for Energy Saving

This section explains the longitudinal control algorithm proposed for saving energy.
If a vehicle wants to spend less energy while driving on an ordinary street, the vehicle should respond flexibly to forward vehicles and signals that obstruct its path.
The proposed longitudinal control algorithm is divided into a velocity pattern generation algorithm for saving energy and an optimal velocity control algorithm, because this simplifies

and clarifies the control structures and enables a flexible response to forward vehicles and signals.
The velocity pattern generation algorithm for energy saving is located at a higher level than the velocity control algorithm. Figure 1 shows the framework of the proposed longitudinal control.
The velocity pattern generation algorithm receives information about the traffic state and blockades for energy saving. This is followed by the generation of approximate upper and lower limit patterns for velocity.
The optimal velocity control algorithm controls motors and brakes by considering the vehicle's efficiency map, gradient, and velocity pattern created by the pattern generation algorithm.
The following subsection gives the details of the velocity pattern generation algorithm and the optimal velocity control algorithm.

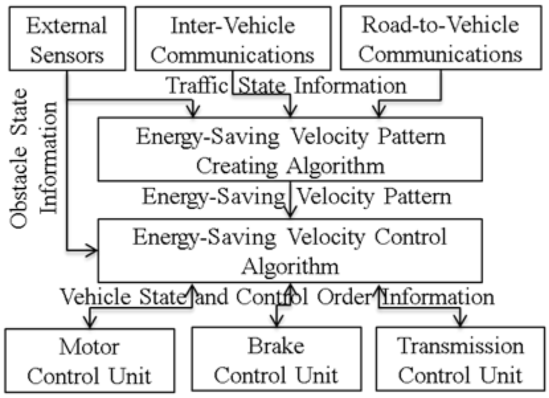

Figure 1: Framework of Energy-Saving Longitudinal Control

2.1 Velocity Pattern Generation Algorithm

The longitudinal control algorithm proposed in this study aims to support a mixed environment in which there are vehicles equipped with only standard features on an ordinary street. In such an environment, it is difficult to predict the future state of all obstacles for saving energy, such as moving or parked vehicles ahead, signal lights at intersections, crossing pedestrians, gradients, or speed limits.
Therefore, in this study, to dynamically support as many obstacles as possible for saving energy, rough upper and lower limit patterns of the velocity are generated by the velocity pattern generation algorithm primarily for saving energy.
The pattern generation algorithm treats all obstacles for saving energy as velocity-position graphs. It impacts a reduction in calculation cost, and the unionization of treatment of obstacles for saving energy. Because the optimal velocity control is located at a lower level, it can find accurate and unique velocity patterns, while the velocity pattern generation algorithm quickly generates approximate upper and lower limit patterns for velocity to save energy while driving.
This study assumes that the driving path and lane are previously known.

2.1.1 Classification of Obstacles for Saving Energy

The control algorithm proposed in this study only controls the longitudinal direction. Thus, forward vehicles, signals, and other obstacles are assumed to reduce vehicle speed and compromise energy-saving driving. All obstacles for energy saving are classified as either foreseeable or unforeseeable.
Unforeseeable obstacles include most obstacles such as forward vehicles equipped with only standard features and common signal lights at intersections. Because unforeseeable obstacles have no special equipment such as vehicle-to-vehicle and road-to-vehicle communication devices, only their current states can be observed by a common external sensor. Common signal lights that cannot share their lighting patterns are also classified unforeseeable obstacles.
On the other hand, foreseeable obstacles correspond to particular obstacles such as signal lights and vehicles. If a signal light has a lightning pattern that, along with its position, can be shared by road-to-vehicle communication preliminarily, it becomes a long-term foreseeable obstacle. Additionally, road-to-vehicle communication can share speed limits along the way. A linked car navigation system may also make a useful contribution.
Additionally, the brake lights and turn signals of a forward vehicle are detected as short term predictions using external sensors. Short-term predictions are classified as foreseeable obstacles.

2.1.2 Velocity Pattern Generation for Unforeseeable Obstacles

As mentioned previously, forward vehicles, signal lights, crossing pedestrians, gradients, and speed limits detected without special equipment such as vehicle-to-vehicle or road-to-vehicle communication are classified as unforeseeable obstacles. For unforeseeable obstacles, the proposed pattern generation algorithm generates upper and lower limit patterns of velocity using the current states of the unforeseeable obstacles as observed by external sensors.

This study presumes that the proposed longitudinal control algorithm is used as a drive assist system, and thus there is a target speed chosen by the driver. If there are no obstacles that require a reduction in speed and compromise energy-saving driving, the proposed velocity pattern generation generates upper and lower limit velocity patterns that adjust the pace to the target speed ordered by the driver. If there are obstacles, the proposed velocity pattern generation algorithm generates upper and lower limit velocity patterns that adjust the pace to reduce energy loss.

As a basic policy of the velocity pattern generation for unforeseeable obstacles, the upper and lower limit velocity patterns adjust the pace to the lowest velocity of the observable obstacles. Figure 2 shows an example of the velocity pattern generation for unforeseeable obstacles. Vehicles A and B, Signals A and B, and the speed limit in the figure can only be observed as current states by external sensors, and cannot be observed as future states. The current states of each obstacle in the figure are as follows: the driver's velocity is set to 70 km/h; the limit velocity is 60 km/h; the velocity of Vehicles A and B is 40 km/h and 50 km/h, respectively; Signal A is green; and Signal B is red.

First, if a vehicle controlled by the proposed longitudinal control algorithm can observe the speed limit, the speed limit is slower than the driver's velocity setting. The speed limit is therefore a priority. At this time, the upper limit pattern reduces the speed to 60 km/h in the most energy-efficient way, such as through free-wheeling or engine braking. After the velocity reaches 60 km/h, the pattern velocity limit is constant.

Second, if the controlled vehicle can observe Vehicle A, Vehicle A has the slowest velocity of all observable obstacles. Thus, if the controlled vehicle remains at over 50 km/h, the controlled vehicle closes in on Vehicle A and will have to reduce its speed rapidly using a mechanical load brake, which increases energy consumption accordingly. Therefore, the controlled vehicle reduces its speed to 50 km/h in the manner previously described.

Third, if the controlled vehicle can observe Signal A, the controlled vehicle ignores its presence as signal A is a green light, which has no substantive meaning.

Fourth, if the controlled vehicle can observe Vehicle B, then Vehicle B has the slowest velocity of all observable obstacles. Therefore, the controlled vehicle reduces its speed to 40 km/h, and avoids colliding with vehicle A in the manner previously described.

Last, if the controlled vehicle can observe Signal B, then Signal B has the slowest velocity of all observable obstacles as it is a red light and is substantively the same as a parked vehicle. Therefore, the controlled vehicle reduces its speed to zero in the manner previously described.

The method described previously may increase energy consumption and generate too great a distance between the controlled vehicle and obstacle, such as a forward vehicle or red signal light. This study adds a condition that, if the controlled vehicle is at a distance at which it will not collide with the obstacle, the controlled vehicle does not consider the obstacle when it reduces its speed to the obstacle's velocity in the most energy-efficient way possible.

Additionally, this study does not consider vehicles behind the controlled vehicle.

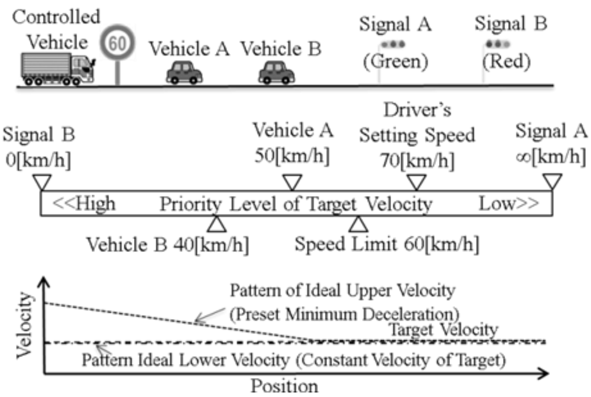

Figure 2: Velocity Pattern Generation for Unforeseeable Obstacles

2.1.3 Velocity Pattern Generation for Foreseeable Obstacles

As mentioned before, particular obstacles that have special equipment such as vehicle-to-vehicle or road-to-vehicle communication, including partial signal lights and other vehicles, are classified as foreseeable obstacles.

If the controlled vehicle can observe foreseeable signals at an intersection, the controlled vehicle can select the proper timing to pass through the intersection and maintain energy saving. Similarly, if the controlled vehicle can observe foreseeable vehicles, the controlled vehicle can calculate new energy-saving velocity patterns without wasting driving efforts.

Figure 3 shows an example of velocity pattern generation for foreseeable obstacles. Vehicle A and Signals A and B in the figure are the observed states of the obstacles from this moment in time onward. The figure shows the velocity pattern of each obstacle observed by the controlled vehicle at this time.

First, in case 1 in the figure, the controlled vehicle can only observe signal A.

To begin with, the generation of an upper limit velocity pattern is described. The controlled vehicle obtains the color of Signal A when the controlled vehicle increases its speed to the driver's pre-set velocity for maximum acceleration. If signal A is green at this time, in the upper limit velocity pattern, the controlled vehicle increases its speed to the driver's velocity setting for maximum acceleration. On the other hand, if signal A is red at this time, in the upper limit velocity pattern, the controlled vehicle increases its speed sufficiently to pass through the intersection before the light changes to red.

At the same time, the controlled vehicle obtains the color of Signal A when the controlled vehicle increases its speed to the driver's pre-set velocity for minimum acceleration. If signal A is green and has the same timing as the upper limit velocity pattern, in the lower limit velocity pattern, the controlled vehicle increases its speed to the driver's velocity setting for minimum acceleration. If signal A is red at this time, in the lower limit velocity pattern, the controlled vehicle increases its speed sufficiently to pass through the intersection before the light changes from green to yellow using the same timing as in the upper limit velocity pattern.

Second, case 2 in the figure shows that the controlled vehicle can observe Signal B. If the controlled vehicle can observe more than two foreseeable signals, this study presumes that the controlled vehicle is driven to the previous signal using the upper limit velocity pattern calculated for the previous signal. In the figure, the controlled vehicle is driven to signal A using the upper limit velocity pattern calculated for signal A. The controlled vehicle then generates the upper and lower limit velocity patterns from Signal A to Signal B in the same way as in case 1. Additionally, if the controlled vehicle path goes through signal A at the next light switch from red to green and signal A has the same timing as described previously, the upper and lower limit velocity patterns are updated. This is done to look for the most energy-saving path.

Third, case 3 in the figure shows that the controlled vehicle can observe Vehicle A. Long-term foreseeable behavior of vehicles is limited on a street mixed with ordinary vehicles. However, if the controlled vehicle can observe the behaviour of Vehicle A through the intersection of Signal B, the upper and lower limit velocity patterns of Signal B are generated in the same manner as in cases 1 and 2 under the condition that the controlled vehicle does not collide with Vehicle A.

Last, the velocity patterns for foreseeable obstacles overlap those of unforeseeable obstacles, and the velocity patterns for all obstacles are the lowest upper and highest lower limit velocity patterns.

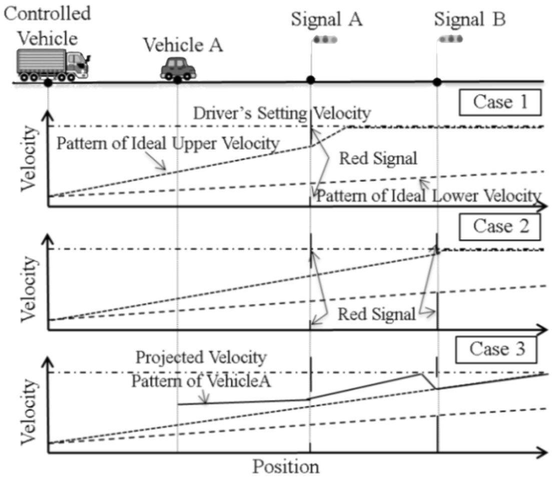

Figure 3: Velocity Pattern Generation for Foreseeable Obstacles

2.2 Optimal Velocity Control Algorithm

The proposed optimal velocity control algorithm solves the optimal control problem of energy consumption for a vehicle from the current time to a previously defined assessment period, and controls the vehicle directly. The optimal velocity control operates under the condition that the vehicle maintains the range between the upper and lower limit velocity patterns calculated by the velocity pattern generation algorithm and does not collide with any obstacles.

Specifically, the optimal velocity control solves the optimal control problem using model predictive control. The control architecture is from reference [3].

Figure 4 shows the relationship between the controlled vehicle and a forward obstacle. The figure expresses the forward obstacle as a passenger vehicle. In addition, the forward obstacle is nearest obstacle and is interchangeable with an intersection with a red signal light.

First, the movement model of the controlled vehicle is expressed according to the following equation.

$$\dot{v}_b = -\frac{1}{m_b} f_{ab} - \frac{1}{m_b} f_{gb} - \frac{1}{m_b} f_{\mu b} + a_b,$$
$$\dot{a}_b = -\tau_b a_b + \tau_b u_b,$$
$$f_{ab} = -\frac{1}{2}\rho A_b C_b v_b{}^2,$$
$$f_{gb} = m_b g \sin\theta(x_b)\,, \tag{1}$$

where v_f and v_b are the velocities of the forward obstacle and controlled vehicle, respectively; a_b is the acceleration of the controlled vehicle; u_b is the drive and brake force of the controlled vehicle; $\theta(.)$ is the road gradient angle; f_{ab} is the air resistance; f_{ub} is the road resistance (constant); m_b is the mass; τ_b is a time constant; ρ is the air density; C_b is the air resistance coefficient; A_b is the frontal projected area; and g is gravity acceleration.

Second, the equations for the state of the controlled vehicle and forward obstacle are as follows.

$$\dot{x} = f(x,u),$$
$$x = [v_f \quad d_f \quad a_b \quad v_b \quad x_b]^T, \qquad u = u_b,$$
$$f(x,u) = \begin{bmatrix} a_f(t) \\ v_f - v_b \\ \frac{1}{\tau}\left(-(a_b + u_b)\right) \\ -\frac{1}{m_b}\left(f_{ab} + f_{gb} + f_{\mu b}\right) + a_b \\ v_b \end{bmatrix} \tag{2}$$

where x is the state vector, u is the input vector, $a_f(.)$ is the acceleration of the forward obstacle, and d_f is the distance between the controlled vehicle and forward obstacle.

Third, the control problem is formulated based on model predictive control. The proposed optimal velocity control algorithm solves the optimal control problem for every control period, and updates input u_b. The assessment function is configured as follows.

$$J = \int_t^{t+T} L dt \tag{3}$$
$$L = w_\varepsilon L_\varepsilon + w_{vu} L_{vu} + w_{vl} L_{vl} + w_{df} L_{df},$$
$$L_\varepsilon = E(u_b, v_b),$$
$$L_{df} = \left\{\frac{1}{2}\left(\sqrt{\left(d_f - d_f{}^*(v_b)\right)^2} + \left(d_f - d_f{}^*(v_b)\right)\right)\right\}^2,$$
$$L_{vu} = \left\{\frac{1}{2}\left(\sqrt{\left(v_b - v_u{}^*(x_b)\right)^2} + \left(v_b - v_u{}^*(x_b)\right)\right)\right\}^2,$$
$$L_{vl} = \left\{\frac{1}{2}\left(\sqrt{\left(v_b - v_l{}^*(x_b)\right)^2} - \left(v_b - v_l{}^*(x_b)\right)\right)\right\}^2 \tag{4}$$

L_ε is a term for assessing the energy consumption of the controlled vehicle. It uses the current energy consumption value calculated based on the velocity and drive force. In addition, L_{vu} and L_{vd} are terms assessing the maintenance of the range between the upper and lower limit velocity patterns. When the current velocity of the controlled vehicle maintains the range between the upper and lower limit patterns, L_{vu} and L_{vd} become zero. In addition, L_{df} is a term that assesses the distance from the obstacle. This study is designed such that if the controlled vehicle comes close to the collision limit distance following the velocity, the controlled vehicle does abruptly decelerate for safety reasons. When the current distance is farther than the collision limit distance, L_{df} becomes zero.

Additionally, W_ε, W_{vu}, W_{vd}, and W_{df} are invariable weight coefficients adjusted by the designer, and T is the assessment period, which is set at 10 s.

Fourth, the following equation creates a condition of constraint to guard from a divergent input:

$$u_b{}^2 \le u_{max}{}^2, \tag{5}$$

where u_{max} is a constant value adjusted by the designer. The following equation expresses the necessary conditions that have to be fulfilled by the optimal input u^* that minimizes J during assessment period T.

$$\dot{x} = H\lambda, \qquad \dot{\lambda} = \frac{\partial H}{\partial x},$$
$$\lambda(t+T) = 0, \quad \frac{\partial H}{\partial u} = 0 \tag{6}$$
$$H = L + \lambda G \tag{7}$$
$$G = u_b{}^2 + u_d{}^2 - u_{max}{}^2, \tag{8}$$

where H is a Hamiltonian matrix, λ is a Lagrange multiplier, and u_d is a dummy variable.

In this study, the proposed optimal velocity control algorithm was developed using the Receding Horizon Control, which is a part of the Model Predictive Control series based on the above solution of the optimal control problem.

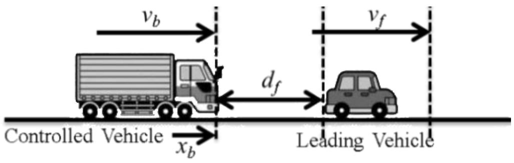

Figure 4: Energy-Saving Velocity Control Algorithm

3 Experimental Evaluation Using Light Electric Vehicles

This study evaluates the proposed longitudinal control algorithm using four light electric vehicles and two signals. Figure 5 shows a photograph of the light electric vehicles. The following subsection describes the conditions, scenario, and results of the experimental evaluation.

Figure 5: Experimental Evaluation Using Light Electric Vehicles

3.1 Experimental Conditions

The implementation site of the experiment is the ring course at Keio University. The four light electric vehicles used are called Vehicles A, B, C, and D. The two signals are termed Signals A and B.

The steering equipment of each vehicle is altered to enable self-steering using a servomotor. During the experiment, the self-steering system follows a prepared trajectory using a RTK-GPS. The reason for this is to prevent the vehicle path from affecting the experimental results.

Vehicles A, B, and C are the forward vehicles. The longitudinal control of these vehicles uses the recorded data of the target drive and brake force values, the velocity, and the position. The recorded data is obtained by human driver previously. The driving and brake forces of Vehicles A, B, and C are controlled by the feedforward of the target drive and brake force values, and the feedback of the velocity and position. The reason for this is to prevent the difference in the behaviour of the forward vehicle from affecting the experimental results.

Vehicle D is the evaluated vehicle. Control of Vehicle D is switchable between the proposed longitudinal control and manual longitudinal control. Vehicle D is driven by two drive motors in the rear wheel, and braked using the regeneration brake of these drive motors. The reason for this is that driving and braking using the drive motors only makes full use of the characteristics of the electric vehicle, while the experiment tried to equalize the experimental conditions between the proposed longitudinal control and manually longitudinal control. In addition, Vehicle D can measure the power-supply voltage and ampere of the inverter of the drive motors.

Signals A and B are located in the middle of two straight sections of the experimental course. Signals A and B have red, yellow, and green lights, and switch lights through a prepared timing sequence.

The longitudinal control system of Vehicle D handles Vehicles A, B, and C as unforeseeable obstacles and can obtain the current velocity and position information of each vehicle during every control period. In addition, the longitudinal control system of Vehicle D handles Signals A and B as foreseeable obstacles and can receive all period information of the nearest forward signal during every control period.

The speed limit on a straightaway of the experimental course is 23 km/h. The speed limit on a curved section of the experimental course is 12 km/h.

Figure 6 shows a sketch of the experimental course.

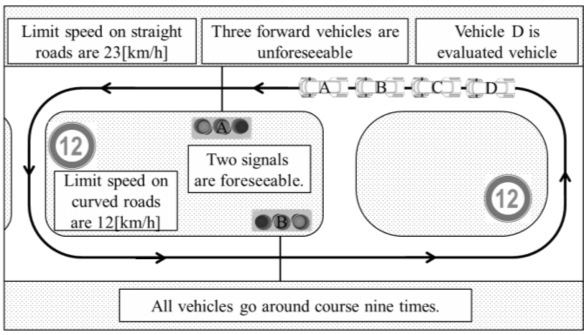

Figure 6: Sketch of the Experimental Course

3.2 Experimental Scenarios

Table 1 lists some of the experimental scenarios.

In the experiment, all vehicles go around the ring course nine times. The travel distance of the vehicles in the experiment at one time is about 2 km.

As mentioned previously, Vehicles A, B, and C are steered, driven, and braked automatically, and accurately repeat the same behavior in each experiment. Signals A and B accurately switch lights using the prepared timing.

For convenience, the following explanation of the experimental scenario curtails descriptions of yellow lights for Signals A and B, as well as certain descriptions of vehicle D.

The experimental scenario is as follows:

Vehicles A, B, C, and D are parked a dozen meters in front of Signal A. After the start of the experiment, Vehicles A, B, and C start moving progressively, and go through signal A, which is green.

Vehicles A, B, and C go through Signal B, which is also green.

Vehicles A, B, and C stop at Signal A, which is red.

Next, Signal A switches from red to green, and Vehicles A, B, and C start moving progressively, going through Signal A.

Because Signal B is late to switch from red to green, Vehicle A reduces its speed inevitably and passingly, and Vehicles A, B, and C go through Signal B.

Because Signal A is late to switch from red to green, Vehicles A, B, and C reduce their speed inevitably and passingly, and go through Signal A.

Vehicles A, B, and C stop at Signal B, which is red.

Next, Signal B switches from red to green, and Vehicles A, B, and C start moving progressively, going through Signal B.

Because Signal A is late to switch from green to red, Vehicles A, B, and C drastically reduce their speed inevitably, and stop at Signal A.

Signal A then switches from red to green, and Vehicles A, B, and C start moving progressively, going through Signal A.

Vehicles A, B, and C go through Signal B, which is green.

Because Signal A is late to switch from green to red, Vehicle A goes through Signal A without reducing speed, and Vehicles B and C reduce their speed inevitably, stopping at Signal A.

Next, Signal A switches from red to green, and Vehicles B and C start moving progressively, going through Signal A.

Vehicles B and C stop at Signal A, which is red, and join Vehicle A.

Signal B then switches from red to green, and Vehicles A, B, and C start moving progressively, going through Signal B. However, Vehicle C is late to start moving, and thus increases its distance from Vehicle B.

Next, Vehicles A, B, and C go through Signal A, which is green. The larger distance between Vehicles B and C remains constant.

Vehicles A, B, and C go through Signal B, which is green. The distance between Vehicles B and C decreases gradually.

Vehicles A, B, and C go through Signal A, which is green. The distance between Vehicles B and C gradually decreases.

Vehicles A, B, and C go through Signal B, which is green. Vehicle C joins Vehicles A and B.

When Vehicles A, B, and C go through Signal A, the signal switches from green to red. Vehicle D, which is driven by a subject goes through or stops at Signal A.

Vehicles A, B, and C stop at Signal B, which is red.

Next, Signal B switches from red to green, and Vehicles A, B, and C start moving progressively, going through Signal B.

If Vehicle D, which is driven by the subject, stops at Signal A, it then starts moving through Signal A after the signal switches from red to green.

Vehicles A, B, and C stop at Signal A, which is red.

If vehicle D, which is driven by a subject, stops at signal B just before going through, signal A switches from green to red. Vehicle D then goes through or stops at signal B.

If vehicle D, which is driven by a subject, is stopped at signal B, vehicle D starts moving and goes through the signal after it switches from red to green.

Vehicle D stops at signal A, which is red, and joins vehicles A, B, and C.

Signal A then switches from red to green, and Vehicles A, B, and C start moving progressively, going through Signal A.

Vehicles A, B, and C go through signal B, which is green.

Vehicles A, B, and C stop at Signal A, which is red.

When Vehicle D stops at Signal A, the experiment is finished.

Table.1: Experimental Scenarios

	Vehicle		
	A	B	C
Sig A Lap 1	Pass	Pass	Pass
Sig B Lap 1	Pass	Pass	Pass
Sig A Lap 2	Stop	Stop	Stop
Sig B Lap 2	Slow	Pass	Pass
Sig A Lap 3	Slow	Slow	Slow
Sig B Lap 3	Stop	Stop	Stop
Sig A Lap 4	Hard Stop	Hard Stop	Hard Stop
Sig B Lap 4	Pass	Pass	Pass
Sig A Lap 5	Pass	Stop	Stop
Sig B Lap 5	Stop	Stop	Stop
Sig A Lap 6	Pass	Pass	Pass
Sig B Lap 6	Pass	Pass	Pass
Sig A Lap 7	Pass	Pass	Pass
Sig B Lap 7	Pass	Pass	Pass
Sig A Lap 8	Pass	Pass	Pass
Sig B Lap 8	Stop	Stop	Stop
Sig A Lap 9	Stop	Stop	Stop
Sig B Lap 9	Pass	Pass	Pass
Sig A End	Stop	Stop	Stop

3.3 Experimental Results

The participants of the experiment included eighteen men and two women. All the participants had a driver's license. The proposed longitudinal control algorithm was evaluated twice.

Figure 7 shows the prepared trajectory followed by all vehicles. As mentioned before, four light electric vehicles and two signals were used in the experiment. The experimental course includes two curves and two straightaways.

Figure 8 shows a point diagram expressing the relationship between the average energy consumption and arrival time at all experimental trials. In the experiment, four subjects ignored the signal once at Sig A Lap 8 or Sig B Lap 8. Compared with the subjects who had driven properly, the energy consumption was reduced by over 12% using the proposed longitudinal control algorithm.

The above results suggest that the proposed longitudinal control algorithm is effective in energy saving.

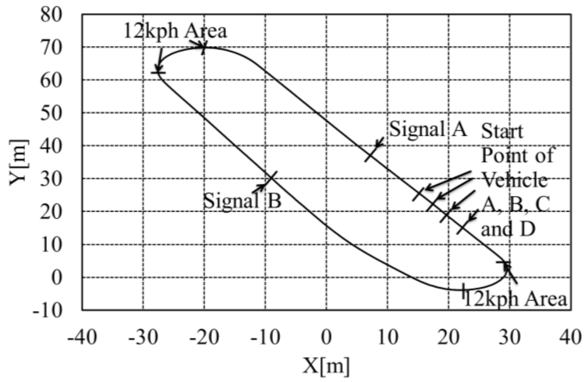

Figure 7: Target Trajectory for All Vehicles

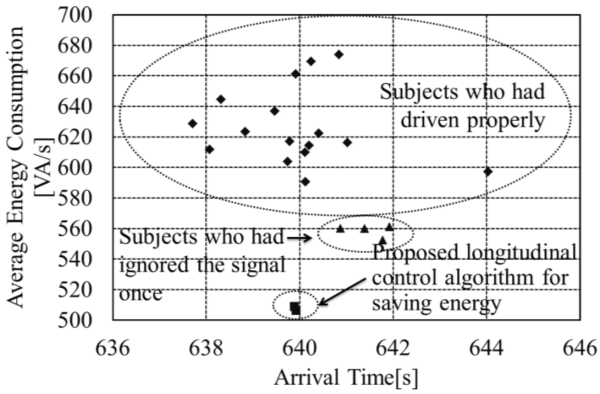

Figure 8: Average Energy Consumption

4 Conclusion

This study proposed a longitudinal control algorithm to save energy in electric vehicles. The algorithm was divided into a velocity pattern generation algorithm to save energy and an optimal velocity control algorithm, because this simplifies and clarifies the control structures and enables a flexible response to forward vehicles and signals.

In the experimental evaluation, the energy consumption was reduced by over 12% using the proposed longitudinal control algorithm as compared with the subjects who had driven properly.

This study suggests that the proposed longitudinal control algorithm is effective in energy saving.

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