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Predictive Eco-cruise Control of Autonomous Vehicle Using a Powertrain Model

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Abstract. This paper aims the implementation of a model based predictive controller for the reduction of fuel consumption, and consequently to improve driving comfort, by applying strategies of ecological driving. Through the use of the route gradient information obtained from digital maps and a GPS module, the predictive controller can compute a sequence of control inputs to smooth the acceleration levels of the vehicle throughout the route, which will reduce fuel consumption. This is accomplished by predictions of the future states of the vehicle based on its dynamics and fuel consumption estimation. A simulation was performed using a real world map information and compared with a fixed speed drive cruise controller. The obtained results showed that fuel economy can be achieved by using the proposed predictive controller in a route with up-down slope.

Keywords. Model predictive control, Fuel economy, Autonomous vehicle.

1 Introduction

The transportation sector currently corresponds for approximately 25% of world energy consumption and CO_2 emissions, taking into account that much of the energy source comes from fossil fuels. Therefore, not only their usage increase the concern about the environmental impact of producing polluting gases, but also raises the cost of oil barrels [10]. There are many aspects that can affect the energy consumption of a vehicle such as weather phenomenons, road surface conditions, driver's behavior, selected driving gear and physical characteristics of the vehicle [2, 11]. The driving behavior also impacts directly on the fuel consumption. To address these problems, the strategies used on eco-driving have recently received great attention.

Eco-driving aims at reducing fuel consumption based on a group of behaviors that can be adopted by the driver. Driving at an even pace, accelerating and braking smoothly and using the correct gears for each situation are some of the strategies that can be adopted [1].

Through the new technologies involving autonomous vehicles, it has been possible to see the decision-making capability shifting from the human driver to the vehicle [4]. This

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way, the processing power existent in autonomous vehicles would allow the implementation of the strategies used on eco-driving in a more efficient way, since it could analyze the information obtained from its environment and current states to compute the best action to be taken. A model-based predictive control (MPC) strategy was chosen to generate the sequence of control inputs, based on the optimization of future states of the vehicle over a prediction horizon.

The main purpose of this paper is to increase fuel economy, using road gradient information obtained from a digital map, a GPS module, a mathematical model of the vehicle dynamics and a fuel consumption estimation. Differently from previous works [1,3] where only a generic vehicle model was used, this paper uses specific vehicle powertrain and fuel consumption models to achieve a better accuracy in the simulation results with a real world system. An illustrated concept of the project is shown in Figure 1.

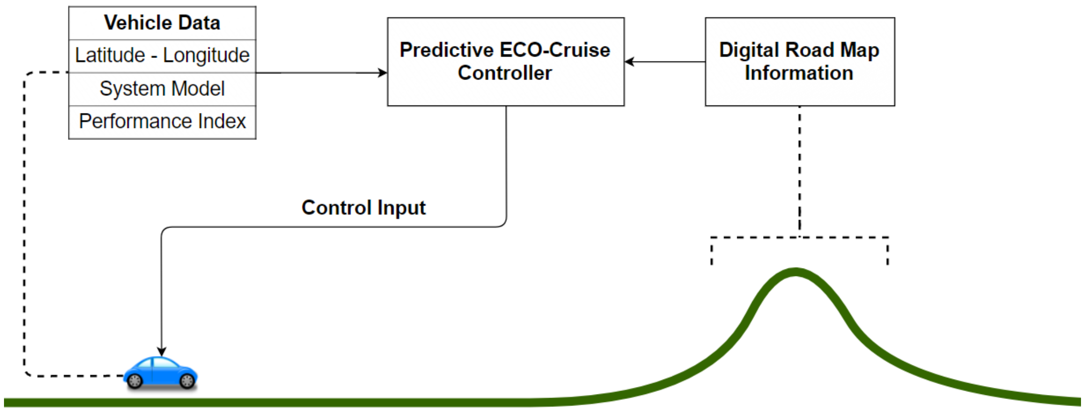

Figure 1: Illustrated concept of the paper.

2 Methods

2.1 Vehicle powertrain model

The powertrain model used in this paper is based on [5] and [9]. These equations use specific vehicle information that are publicly available. The equation (1) represents the engine speed ω_e any instant t, where $v(t)$ is the vehicle velocity (km/h), ξ_0 the current gear ratio, r the wheel radius (m), i tire slippage (%), ω_{idle} and ω_{red} are the idle and redline engine speed (rpm), respectively.

$$\omega_e(t) = \min\left(\max\left(\frac{1000v(t)\xi_0}{120\pi r(1-i)}, \omega_{idle}\right), \omega_{red}\right) \quad (1)$$

The engine power at a specific engine speed $P_e(\omega_e)$ is calculated as

$$P_e(\omega_e) = (P_{max}/\omega_p)\omega_e + (P_{max}/\omega_p^2)\omega_e^2 - (P_{max}/\omega_p^3)\omega_e^3, \tag{2}$$

where P_{max} is the maximum engine power (kW) and ω_p the engine speed (rpm) at peak power. The actual power available is obtained by a linear relationship between the percentage of throttle $f_p(t)$ and the proportion of maximum power. The throttle position $f_t(t)$ ranges between f_{min} and f_{max}, which can be assumed to be approximately 10-15% and 90-100% [9]. Therefore, $f_p(t)$ can be calculated as

$$f_p(t) = 0.01(f_{max} - f_{min})^{-1}[(100 - f_{min})f_t(t) - (100 - f_{max})f_{min}]. \tag{3}$$

The driveline propulsive force $F(t)$ (N) is given by equation (4), where η_d is the driveline efficiency, m_{ta} the mass on the propulsive axle, μ the coefficient of road adhesion and g the gravitational acceleration. $F(t)$ must be less than $g \cdot m_{ta}\mu$, which is the maximum frictional force that can be sustained between the vehicle's wheels and the road surface.

$$F(t) = \min\left[3600 \cdot \eta_d \frac{f_p(t)P_{max}(\omega_e)}{v(t)}, g \cdot m_{ta}\mu\right] \tag{4}$$

The resulting resistance force acting on the vehicle $R(t)$ (N) is given by equation (5), where ρ (kg/m^3) is the density of air at sea level, C_D the drag coefficient, C_h the correction factor for altitude, A_f (m^2) the vehicle frontal area, m the vehicle mass (kg) and C_r, c_5, and c_6 are rolling resistance coefficients associated with road parameters.

$$R(t) = (\rho/25.92)C_D C_h A_f v(t)^2 + g \cdot (m/1000)C_r[c_5 v(t) + c_6] + g \cdot m \sin(\theta(x)) \tag{5}$$

The gradient angle $\theta(x)$ (rad) related to the road altitude R_{alt} (m) obtained from the digital map data and the current position of the vehicle x (m) is given by

$$\theta(x) = \tan^{-1}\left(\frac{R_{alt}(x + \Delta x) - R_{alt}(x - \Delta x)}{2\Delta x}\right). \tag{6}$$

The state vector of the system is defined as $\zeta = [x(t) \quad v(t)]^T$ and the control input as $u = [f_t(t)]$. Therefore, the state equation can be defined as $f(\zeta, u) = [v(t) \quad a(t)]^T$, where the acceleration $a(t)$ (m/s^2) is calculated as

$$a(t) = \frac{F(t) - R(t)}{m(1.04 + 0.0025\xi_0(t)^2)} \tag{7}$$

2.2 Fuel consumption model

The fuel consumption model $FC(t)$ (liters) used in this work is the VT-CPFM-2, developed by the Virginia Tech Transportation Institute [8]. Detailed information on the equations used to obtain the vehicle specific model parameters can be found in [7,8]. The main advantage of this model is that its calibration can be done by using publicly available data of the vehicle.

$$FC(t) = \beta_0\omega_e(t) + \beta_1 P(t) + \beta_1 P(t)^2 \tag{8}$$

2.3 Nonlinear predictive controller

The C/GMRES method [6] is used to generate the sequence of optimal control input based on a performance index, for a prediction horizon T discretized into N steps of size k, from a virtual time $t' = nk$ to $t' = nk + T$. It does not require much computational power since it does not use iterative searches, which allows its implementation in real time.

The cost function L used in the performance index is

$$L = w_1 \cdot FC(t) + w_2 \cdot \left[\frac{1}{2}(a(t) + g\sin(\theta(x)))^2\right] + w_3 \cdot \left[\frac{1}{2}(v(t) - v_d)^2\right], \tag{9}$$

where v_d is the desired constant velocity for segments without up-down slope. The cost function L is divided in three terms, weighted by the constants w_i. The first term defines the cost of the fuel consumption rate of the vehicle at any instant t. The second part of corresponds to the acting forces on the vehicle, such as acceleration and gravitational force due to the road slope. This term is important to help maintain the magnitude of acceleration and braking inputs as minimum as possible when varying the road elevation. The last part is used to maintain the vehicle at a desired velocity.

The optimal control input can be obtained using the Hamiltonian function shown in equation (10), composed of the state equation $f(\zeta, u)$, the cost function L, the costates λ and μ, the Lagrange multiplier associated with a constraint C.

$$H(x, \lambda, u, \mu) = L(x, u) + \lambda^T f(\zeta, u) + \mu^T C(x, u). \tag{10}$$

The discretized conditions for optimality are:

$$\zeta^*_{i+1}(t) = \zeta^*_i(t) + f(\zeta^*_i(t), u^*_i(t), p(t + i\Delta\tau))\Delta\tau, \quad \zeta^*_0(t) = \zeta(t), \tag{11}$$

$$\lambda^*_i(t) = \lambda^*_{i+1}(t) + H^T_\zeta(\zeta^*_i(t), \lambda^*_{i+1}(t), u^*_i(t), \mu^*_i(t), , p(t + i\Delta\tau)) \tag{12}$$

$$H^T_u(\zeta^*_i(t), \lambda^*_{i+1}(t), u^*_i(t), \mu^*_i(t), , p(t + i\Delta\tau)) = 0 \tag{13}$$

$$C(\zeta^*_i(t), u^*_i(t), \mu^*_i(t), , p(t + i\Delta\tau)) = 0, \tag{14}$$

where $p(t)$ represents time-varying parameters.

3 Results

A simulation of the proposed eco-cruise control (E-CC) controller was performed by comparing its results with a fixed speed drive controller (FS-CC) [1], which maintain the vehicle with a desired velocity for the entire route. It is assumed that the vehicle starts at 80 km/h and only uses the fifth gear, since it is already at a high speed. The algorithms were evaluated on a 32 km virtual road scenario, with its elevation profile presented in Figure 2. Only the longitudinal forces acting on the vehicle were considered during the simulation. The parameters used for calibration of the models used and for the MPC controller are shown in Table 1

Figure 2 shows the simulation results, where the blue line represents the predictive eco-cruise controller and the red line the fixed speed drive. A detailed comparison of the obtained results is presented in Table 2.

Table 1: Simulation parameters.

Description	Parameter	Value
Prediction horizon	T	10 s
Step size	k	0.1 s
Vehicle mass	m	1206 kg
Frontal area of the vehicle	A_f	2.32 m^2
Wheel radius	r	0.381 m
Driveline efficiency	η	0.94
Maximum vehicle power	P_{max}	95.6 kW
Engine speed at P_{max}	ω_p	5250 rpm
Engine speed at T_{max}	ω_t	4500 rpm
Engine speed at idle	ω_{idle}	850 rpm
Cost function weights	w_1	1000
	w_2	50
	w_3	0.80
Fuel consumption model constants	β_1	1.791×10^{-7}
	β_1	8.284×10^{-5}
	β_2	1×10^{-6}
Fifth gear ratio	ξ_0	0.909
Desired constant velocity	v_d	80 km/h

Table 2: Detailed comparison of simulation results for the E-CC and FS-CC controllers.

Description	E-CC	FS-CC
Road length	32 km	
Total fuel consumption	1.21 liters	1.33 liters
Average fuel consumption	26.40 km/L	24.00 km/L
Time to finish route	24.62 min	23.96 min
Economy of E-CC	9.12%	

4 Discussion and Conclusion

The proposed predictive eco-cruise and a fixed speed drive controllers were simulated and compared on a 32 km route, assuming that only the longitudinal forces acting on the vehicle were present. The control input assumes that whenever a negative input is calculated, the brake pedal is used instead of the accelerator.

The results showed that the E-CC controller could achieve 9.12% of fuel economy in comparison with the FS-CC, which was possible by reducing the amplitude of acceleration and braking levels during up-down slope sections. Based on the elevation data obtained

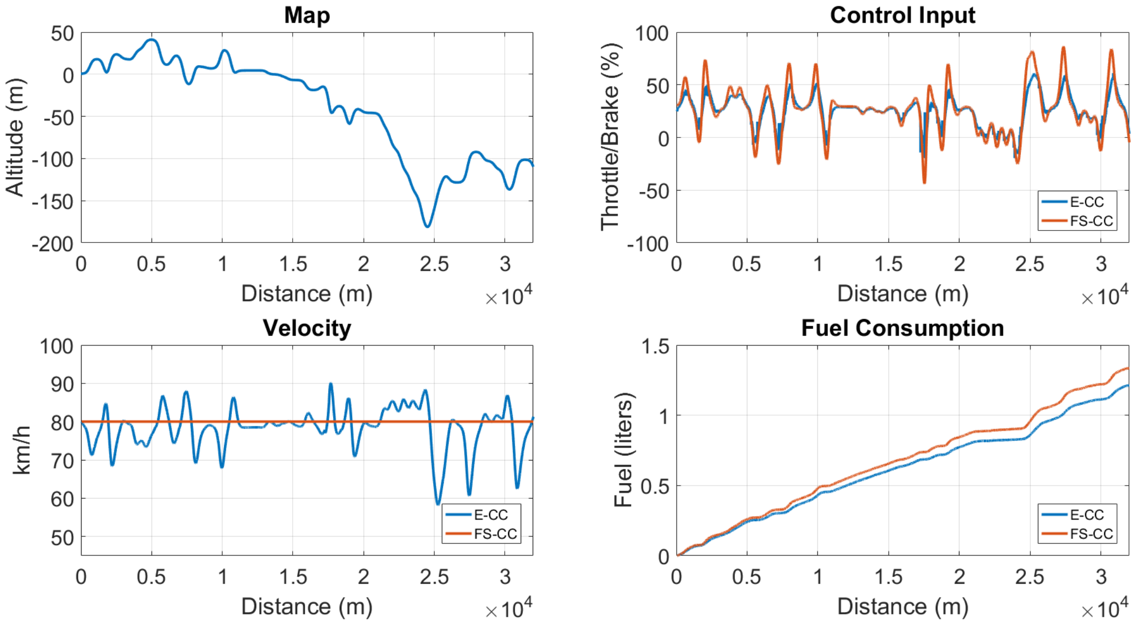

Figure 2: Results obtained for the E-CC and FS-CC controllers in the simulation.

from the digital map of the route and the vehicle position from the GPS module, the E-CC controller increases the velocity of the vehicle before entering an uphill section, which reduces the acceleration effort during the ascension. At downhill sections, the E-CC uses the gravitational force acting on the vehicle to gain velocity without requiring to the vehicle engine power. Consequently, the driver comfort is increased, since it is directly related with the acceleration amplitude. The predictive controller computes the control input through optimizations of the future states of the vehicle, based on a specific powertrain and fuel consumption models. The time required for both controllers to finish the route was also similar, approximately 40 seconds longer for the E-CC, which proves that fuel economy can be achieved without great impact on the travel duration.

Future works include considering the lateral forces acting on the vehicle and the implementation of the proposed predictive eco-cruise controller in an autonomous vehicle.

References

[1] M. A. S. Kamal, M. Mukai, J. Murata, and T. Kawabe, Ecological vehicle control on roads with up-down slopes, IEEE Transactions on Intelligent Transportation Systems, vol. 12, no. 3, 783–794, (2011), DOI: 10.1109/TITS.2011.2112648.

[2] M. A. S. Kamal, M. Mukai, J. Murata, and T. Kawabe, Model predictive control of vehicles on urban roads for improved fuel economy, IEEE Transactions on Control Systems Technology, vol. 21, no. 3, 831–841, (2013), DOI: 10.1109/TCST.2012.2198478.

[3] Y. C. Lin and H. L. T. Nguyen, Development of an eco-cruise control system based on digital topographical data, Inventions, vol. 1, no. 3, 19–35, (2016), DOI: 10.3390/inventions1030019.

[4] A. C. Mersky and C. Samaras, Fuel economy testing of autonomous vehicles, Transportation Research Part C: Emerging Technologies, vol. 65, 31–48, (2016), DOI: 10.1016/j.trc.2016.01.001.

[5] D. Ni and D. Henclewood, Simple engine models for vii-enabled in-vehicle applications, IEEE Transactions on Vehicular Technology, vol. 57, no. 5, 695–2702, (2008), DOI: 10.1109/TVT.2008.917229.

[6] T. Ohtsuka, A continuation/gmres method for fast computation of nonlinear receding horizon control, Automatica, vol. 40, no. 4, 563–574, (2004), DOI: 10.1016/j.automatica.2003.11.005.

[7] S. Park, H. Rakha, K. Ahn, and K. Moran, Virginia tech comprehensive power-based fuel consumption model (vt-cpfm): model validation and calibration considerations, International Journal of Transportation Science and Technology, vol. 2, no. 4, 317–336, (2013), DOI: 10.1260/2046-0430.2.4.317.

[8] H. A. Rakha, K. Ahn, K. Moran, B. Saerens, and E. Van den Bulck, Virginia tech comprehensive power-based fuel consumption model: Model development and testing, Transportation Research Part D: Transport and Environment, vol. 16, no. 7, 492–503, (2011), DOI: 0.1016/j.trd.2011.05.008.

[9] H. A. Rakha, K. Ahn, W. Faris, and K. S. Moran, Simple vehicle powertrain model for modeling intelligent vehicle applications, IEEE transactions on intelligent transportation systems, vol. 13, no. 2, 770–780, (2012), DOI: 10.1109/TITS.2012.2188517.

[10] W. F. Schmitt, Metodologia de Avaliação de Eficiência Energética em Veículos Leves e seus Impactos em Termos de Uso de Combustíveis, Ph.D. dissertation, Universidade Federal do Rio de Janeiro, (2010).

[11] A. Vaezipour, A. Rakotonirainy, and N. Haworth, Reviewing in-vehicle systems to improve fuel efficiency and road safety, Procedia Manufacturing, vol. 3, 3192–3199, (2015), DOI: 10.1016/j.promfg.2015.07.869.