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Approach for modelling and controlling of autonomous cruise control system through machine learning algorithms

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ABSTRACT

Automated cruise control installation is one of the utmost significant phases in the auto industry's pursuit of autonomous vehicles. The controller of choice is one of the key factors in determining whether a design will be durable and cost-effective. The model-based controller and a cutting-edge algorithmic optimization method are both presented inside the framework of this proposed study. The suggested controller may achieve the desired characteristics of the design, including a faster rise time, a faster settle time, a smaller peak overshoot, and a smaller steady-state error. A MATLAB-executed and -simulated system model using a control method based on a hybrid genetic algorithm and reinforcement learning has been used to effectively and automatically regulate the vehicle's velocity in compliance with all design parameters.

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1. INTRODUCTION

An automatic cruise control system seeks to keep the car travelling at a constant pace regardless of the conditions on the road. The quickest way to accomplish this objective in less than ten years is to implement a mixture of P, I, and D controllers. In spite of this, the proportional integral derivative (PID) controller performs poorly under rapid set point tracking operation conditions. As a direct result, the model predictive controller, a model-based controller, was created to efficiently control the vehicle's speed. Improved set point monitoring and reduced fuel consumption are also outcomes of using this control technique. Following completion of the optimization procedure, the model and controller parameters will have been appropriately chosen. The cruise control system must be able to be turned off both explicitly and automatically when the driver depresses the brake and, in some circumstances, the clutch. This is a requirement for all cruise control systems. It typically comes with a memory feature that allows the user to restart the set speed after applying the brakes, as well as a coast mode that allows the user to drop the set speed without applying the brakes. Even with the cruise control enabled, the driver is still able to accelerate the vehicle by using the throttle pedal; however, once the pedal is released, the vehicle will decelerate until it reaches the speed that was previously set.

The cruise control system in a car will unintentionally modify the speed as it is moving down the road. This technique used an electric motor with a bi-directional cruise drive to adjust the throttle position and determine ground speed based on driveshaft rotations [1]. The bulk of the time, PI or PID controllers are used in cruise control systems with adaptive cruise control (ACC). To ensemble the needs of the cruise control system, this work will demonstrate how to change the structure and settings of the controller. A distinct controller structure is needed for step changes in speed compared to linear speed fluctuations, which call for an entirely different structure.

Information for the control system comes from on-board sensors. The Mitsubishi Debonair lidar-based distance sensing system was the first commercial system to be put into operation. It was created by the company. This technology did little more than notify the driver; it did not affect the acceleration, braking, or gear shifting in any way. The Mercedes-Benz S-class W220 was the first commercial vehicle to feature a radar-assisted adaptive cruise control system when it debuted [2]. A PID controller or similar just a feed forward system may be used to construct the control logic for the cruise director [3].

2. SYSTEM MODELLING AND THEORETICAL ASSUMPTIONS

One noteworthy illustration of a feedback control arrangement that is included in numerous contemporary cars is automated cruise control [4], [5]. This explicit system is present in a wide range of automobiles. The fundamental goal of the cruise control system is to keep the vehicle moving at a constant pace independent of any changes to the surrounding environment, such as changes in the wind's direction and speed or the road's gradient. Figure 1 depicts the free body diagram of cruise control system.

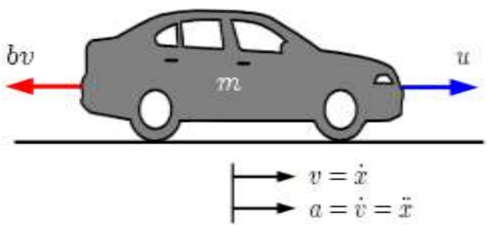

Figure 1. Cruise control system of car movement

Ignoring external influences such variations in wind speed or direction and road orientation, the cruise control maintains the car moving at consistent pace. The vehicle's speed is gauged (often on the driveshaft) and contrasted with the target speed. The separation between the two following cars is s [m]. The first order difference equation for the moving object is based on 2nd law of newton shown in (1):

$$m.\frac{dv(t)}{dt} + b.v(t) = u(t) - p(t) \tag{1}$$

The transfer function S(s) of the moving vehicle is obtained by applying the L-transform to (1) gives in (2).

$$S(s) = \frac{1}{m.s+b}\left(U(s) - P(s)\right) = \frac{K}{T_{s+1}} \text{ (Laplace transform of u(t) - Laplace transform of p(t))}$$

$$S(s) = \frac{V(s)}{U(s)} = \frac{1}{m.s+b} = \frac{K}{T_{s+1}} \tag{2}$$

Derive the following gain values using the standards for b=50 [Nsm(-1)], nominal control force u=500 [N], and m=1,000 [kg]. K parameter=0.02 [λ.m $(N^s)^{-1}$] and T=20 sec.

3. RESULTS AND DISCUSSION SYSTEM ANALYSIS

It is important to discuss the design requirements that the compensated system needs to fulfill in order to be successful. Because of this, the required open loop step response [6], [7] will take place when the engine finally runs out. The car will then attain its maximum velocity. When driving a car, the time it takes to reach full acceleration should be less than seconds. The items listed below are some of the criteria that must be satisfied.

- Rise time <8 s
- Overshoot <15%
- Steady state error <3%

3.1. The linear control and disturbance signal's tracking

It is important to modify arrangement and factors of the controller is to track signal linearly growing or decreasing as shown in the picture. It is essential that F(s) be constant, 2nd order transfer function and that 1 - F(s) reflect a second derivative. F(s=0)=1.

$$F(s) = \frac{a_1 s+1}{a_{2S^2+a_1 s+1}} = \frac{\frac{4}{3}\lambda s+1}{(1+\lambda s)\left(1+\frac{\lambda}{3}s\right)} = \frac{\frac{4}{3}\lambda s+1}{\frac{1}{3}\lambda^2 s^2+\frac{4}{3}\lambda s+1} \tag{3}$$

Controller design parameter as shown in (4).

$$\frac{R_{M(s)}=\frac{F(s)}{1-F(s)}1}{M(s)} = \frac{\frac{4}{3}\lambda s+1\frac{\beta(\ \ )}{\frac{1}{3}\lambda^2 s^2}\left(\frac{T}{4}s+1\right)}{1} = \frac{\frac{1}{3}\lambda\beta T s^2+s\beta\left(\frac{4}{3}\lambda+\frac{T}{4}\right)+1}{\frac{1}{3}\lambda^2 s^2} \tag{4}$$

Figure 2 shows a simulation of the system's open-loop reaction in the absence of feedback control in response to a 500 N step input intensity. It should be emphasized that the open-loop system lacks oscillations and other characteristics common to first-order systems. The open-loop system also succeeds in reaching the target steady-state speed of 10 m/s, but the rising time, which is roughly 60 seconds, is considerably too sluggish. It is must to acquire a feedback controller that can considerably speed up response time without adversely affective the many different dynamic implementation parameters [8]. It is observed that the open-loop system is stable and does not oscillate since the pole is both real and negative as shown in Figure 3. This is due to the pole's reality. Additionally, how quickly the system reacts depends on the magnitude of this pole, shown by the symbol b/m: the greater the level, the faster the system advances the value at the steady-state. We can see that the first-order system features are clearly visible in the bode plots as shown in Figure 4. At the corner frequency of w=b/m=0.05 rad/s, these features include a amount of -3 dB, a phase of -45 deg, and a roll-off at high frequencies of -20 dB/dec.

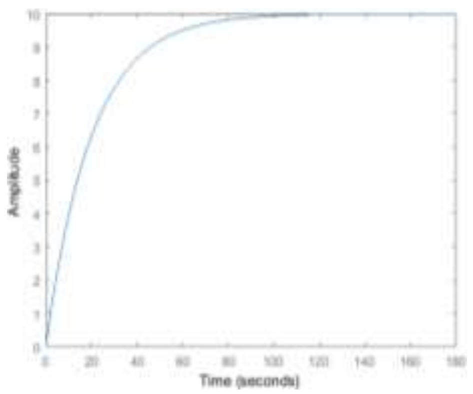

Figure 2. Step response at open loop condition

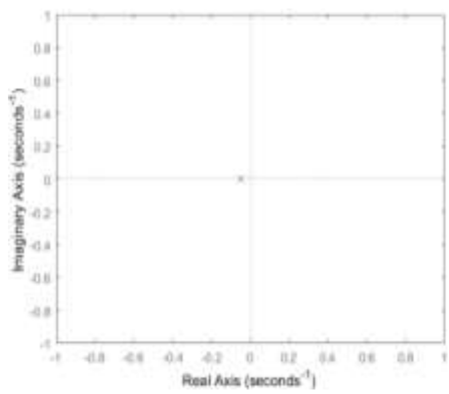

Figure 3. Pole-zero mapping on s-plane

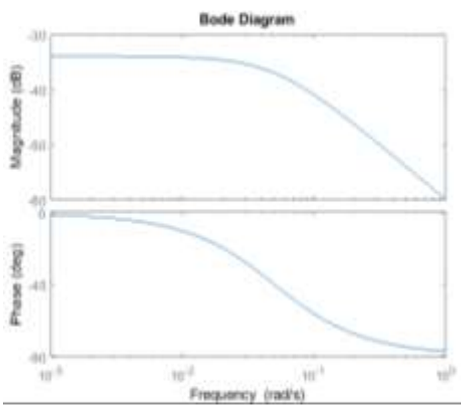

Figure 4. Frequency response at open loop

4. LEARNING BASED HYBRID–OPTIMIZATION TECHNIQUE

4.1. Genetic

A approach that is based on experience and is used to find solutions to optimization problems is a genetic algorithm, or GA. This is a heuristic search that the algorithm uses to simulate the natural process of genetic selection [9]. The solution to optimization problems can be developed by applying methods like selection, crossover, and mutation, which are inspired by the process of natural evolution. GAs begins with an initial set of viable solutions (the population or individuals) to a particular problem (the environment). Each individual in the population is represented by some type of encoding termed a "chromosome". These chromosomes are put through a series of tests inside the problem area to discover whether or not they have the ability (fitness) to produce an optimal solution to the problem. (The extent to which the people they represent have a suitable relationship with the environment). Chromosomal fitness is the criterion that is utilized by the selection operator in order to choose a certain set of chromosomes from the reproductive population (the fittest survival). The process of reproduction typically includes two different types of GA operators, such as crossover and mutation, which work together to make new humans by combining the information that is found in the chromosomes that are chosen. In the problematic area, the newly arrived people are put to the test, and the procedure is carried out again and again until the necessary circumstances are met [10], [11]. In the realm of engineering, the GA is frequently applied to the resolution of exceedingly tough problems of search and optimization that are challenging to manage with empirical or straightforward enumeration techniques. Even if the method does not produce a solution that is perfect, it is sufficient for accomplishing a number of goals.

4.2. Reinforcement learning algorithm

The concept of machine learning was initially put forth in [12], the fields of artificial intelligence and computer games. The machine learning algorithm assisted the computer in making it possible for the system to learn from the data, which then enabled the system to predict the output by making use of the data that had been learnt from the input. The development of an algorithm that is capable of making decisions regarding the output based on the input data that is received from the system is a necessary prerequisite for the field of machine learning. Machine learning is a subfield that falls under the umbrella of artificial intelligence [13], [14]. The machine learning system is capable of learning in three distinct ways, each of which is determined by the character of the answer that is produced. Managed learning, unverified learning, and reinforcement learning are the three groupings of machine learning.

The agent in reinforcement learning has a set of rules and several algorithms that can be used for the process of self-learning. The agent's policy serves as the system's controller. The agent is expected to function by picking up knowledge from its surroundings by observing the condition of the input at any given time. Based on the observed input, the agent can then choose an appropriate course of action or response for the related system is shown in Figure 5.

Figure 5. General structure of reinforcement learning control algorithm

All potential parameters, excluding the controller, are included in the reinforcement learning environment. The agent's environment may contain the plant, a reference signal, a computed error, a disturbance signal, filters, and analog-to-digital or analog-to-digital converters. Generally speaking, observation refers to the agent's quantifiable response to the environment [15], [16]. With the aid of system-observed parameters, the agent is able to conduct actions [17]. The rewards for each observation from the model can be calculated to determine the action's correctness. Both the positive response and the negative response can be used to calculate the rewards. The agent will include prizes for a favorable or accurate prediction and penalties for a negative or incorrect prediction. The steady state inaccuracy, which is the result of negative acts, might increase the overall effectiveness of action identification.

Robotics, linear, and nonlinear process control applications are only a few examples of controller problems where reinforcement learning is effectively applied. Moreover, reinforcement learning will make the system to effectively act whenever the real world environment changes. The existing controller does not work for the real time dynamic changes with minimal offset error [18]. It is possible to use gain scheduling, robust control, and nonlinear predictive control. The algorithm for reinforcement learning was self-taught. It is possible to utilize it to create an end-to-end model controller that creates the actions right from the raw data.

The reinforcement learning-based controller aims to regulate the plant states "s" of a processing plant by performing control actions as an agent "a" that are dependent on the present state of input data. When the controller "a" performs action, the states "s" gather the reward as R. (s, a). Based on the probability distribution function Psa(s') or deterministically based on the state transition law as s' = f, it depends typically on both action and state (s, a). The action sequence or best course of action in the equation's $V^{\pi}(S)$ is thought to maximize the plant's cumulative rewards as shown in (5).

$$V^{\pi}(S) = E.[R(S_0) + \gamma.R(S_1) + \gamma^2.R(S_2) \dots.[s_0 = s \; and \; \pi] \quad (5)$$

Where $V^{\pi}(S)$ is denoted as discounted reward as the initial state of s0 and $\pi(s) - S$ sequence of action performed in each state. γ=Policy coefficient and the range of$\gamma\epsilon[0,1)$. The Markov decision process (MDP), which is comprised of the five tuples S, A, Psa, and R, is the foundation for choosing the best course of action. The recompense function is characterised by $R: S \times A \rightarrow \mathbb{R}$.

The current state can be mapped to the action by using policy π is a function$\pi: S \rightarrow A$. The optimal policy $\pi * (s)$ is the strategy that increases the total payoff as shown in (6).

$$\pi * (s) = {}^{max}_{\pi} V^{\pi}(s).V^{\pi}(s) \quad (6)$$

Once the best course of action has been taken and the Bellman equation has been satisfied, the optimal value function can be determined as shown in (7).

$$V^*.(s) = R\,(s) + {}^{\max}_{a\in A}\gamma \sum_{S'\in S} P_{sa}\,(s').V^*\,(s') \quad (7)$$

In (8) is used iteratively in the value iteration approach to determine the ideal value function, with the estimation starting at zero. The best policy can be calculated when the best value function has been identified.

$$\pi^*(s) = {}^{argmax}_{a\in A} \sum_{S'\in S} P_{sa}(s')V^*(s') \quad (8)$$

The data must discretize the action and state for RL to be applied to the liquid level system. The generalised ability of artificial neural networks (ANN) to lessen the impact of state discretization produces outcomes with fewer oscillations and overshoot of the liquid level and temperature. In (9) and (10) provide the potential reward point

$$R(h) = -C\|h_{desired} - h\| \; and \;\; R(h) = -C\|T_{desired} - T\| \quad (9)$$

$$R(h) = \begin{cases} -1, if\|h_{desired} - h\| \geq \delta \\ 0, \qquad\qquad otherwise \end{cases} and \;\; R(h) = \begin{cases} -1, if\|T_{desired} - T\| \geq \delta \\ 0, \qquad\qquad otherwise \end{cases} \quad (10)$$

Up until the desired state is attained and it is given in equation, the process is repeated with each subsequent action as shown in (11).

$$[h_1(0)] \xrightarrow{q_1.(0)} [h_1(1)] \xrightarrow{q_1.(1)} [h_1(2)] \xrightarrow{q_{1.(2)}} \text{and} \; [T_1(0)] \xrightarrow{q_1.(0)} [T_1(1)] \xrightarrow{q_1.(1)} [T_1(2)] \xrightarrow{q_{1.(2)}} \quad (11)$$

With control action the total payoff is given in (12)

$$\begin{aligned} &V(h) = R\big(h(0)\big) + \gamma R\big(h(1)\big) + \gamma^2 R\big(h(2)\big) + \text{and} \\ &V(T) = R\big(T(0)\big) + \gamma R\big(T(1)\big) + \gamma^2 R\big(T(2)\big) + \end{aligned} \quad (12)$$

In (13) contains the value function for the fixed policy starting from the initial state.

$$V^{\pi}(h) = E\big[R.\big(h(0)\big) + \gamma.R.\big(h(1)\big) + \gamma^2.R.\big(h(2)\big) + \cdots.\big]h(0) = h,\pi \text{ and}$$
$$V^{\pi}(T) = E\big[R.\big(T(0)\big) + \gamma.R\big(T(1)\big) + \gamma^2.R\big(T(2)\big) + \cdots.\big]T(0) = T,\pi \quad (13)$$

This relationship also given by using Bellman as (14).

$$V^{\pi}(h) = R(h) + \gamma V^{\pi}(h') \ \ and \ \ V^{\pi}(T) = R(T) + \gamma V^{\pi}(T') \quad (14)$$

The final optimum solution for the updated control move is given in (15).

$$V^{*}(h) = {}^{max}_{\ \pi}V^{\pi}(h) = R(h) + {}^{\ max}_{q_1 \in Q_1}\gamma V^{*}(h') \quad (15)$$

The best policy of the process dynamics at any state of level and temperature is given in (16).

$$\pi^{*}(h) = {}^{argmax}_{q_1 \in Q_1}V^{*}(h') \ and \ \ \pi^{*}(T) = {}^{argmax}_{q_1 \in Q_1}V^{*}(T') \quad (16)$$

5. CONTROLLER DESIGN

5.1. Conventional PID controller

The PID controller is utilized frequently due to the fact that it is easy to comprehend and is quite efficient [19]. Because all engineers have a conceptual understanding of differentiation and integration, the PID controller has the advantage of allowing them to build the control system even if they do not have a broad understanding of control model. In addition, despite its seeming lack of complexity, the compensator is extremely ingenious since it both remembers the past behavior of the system (by integration) and projects what that behavior will be in the future (through differentiation). The response of the conventional PID controller [20], [21] tuned with parameters of reference speed is given in the Figure 6. The mathematical expression of PID controller is shown in (17).

$$C(s) = K_p + \frac{K_i}{s} + K_d s = \frac{K_p s + K_d s^2 + K_i}{s} \quad (17)$$

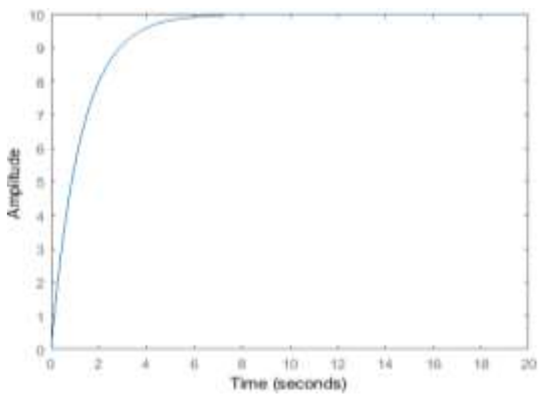

Figure 6. Closed loop PID step response of cruise control system for the reference speed of 10 m/sec

5.2. Adaptive cruise controller with collision avoidance

The control system was developed to make driving in regular, safe conditions more comfortable for the driver, and it also eliminates the risk of rear-end collisions in instances where the car is following another vehicle. When it comes to driving, things may be broken down into three categories: safe, warning, and dangerous. It has been suggested to use one of three distinct control tactics based on the circumstances of the drive [22], [23]. The establishment of driving scenarios involves the utilization of a non – dimensional warning index, in conjunction with the time to collision matrix (TTC) [24]. The suggested ACC/CA (collision avoidance) system makes use of manual driving data and a confusion matrix in order to fine-tune the control parameters. This ensures that the system does not experience any collisions [25]. The subject vehicle's data on following other vehicles was compared to data collected from actual, manual driving situations in the real world. The ACC system was, as final step, installed in a functioning car and put through its paces in simulated and real-world driving conditions, respectively. The proposed control strategy shown in Figure 7 will provide natural following capabilities that are akin to human manual driving in a wide range of driving scenarios, including high-speed driving and low-speed stop-and-go situations. The host's speed automatically reduces if the distance is less than Δ_{shr}, when the target speeds up, ARO(s) speeds up the host as well, all the way to $V_{1zet}(t)$. For the well-ordered system of the reworking part of the system shown in (18).

$$\frac{d\Delta s(t)}{dt} = v_2(t) - v_1(t) \qquad (18)$$

Using the Laplace transform on (18), we now get in (19).

$$\Delta s(s) = \frac{1}{s}(v_2(s) - v_1(s))\ ;\ S_A(s) = \frac{\Delta s(s)}{V_1(s)} = \frac{1}{s} \qquad (19)$$

Let $\Delta s(t) = \Delta_{shr} + \Delta(t)$.
By altering the controller for the disturbance's structure and parameters, zero steady state error can be achieved for vehicle distance. It can raise the order of F(s) to the second order while keeping the characteristics of M_A (s) shown in (20). It is appropriate to follow the parameters and structure.

$$F(s) = \frac{1+s2\lambda}{1+s2\lambda+s^2\lambda^2}$$
$$M_A(s) = \frac{F(s)}{1-F(s)}\frac{1}{M(s)} = \frac{1+s2\lambda}{s^2\lambda^2}\frac{1+s\tau}{\beta} = \frac{1+s(2\lambda+\tau)+s^2 2\lambda\tau}{s^2\beta\lambda^2} \qquad (20)$$

Designing the disturbance observer will produce results similar to those in the prior situation is the objective. Therefore, define the place of M_A (s).

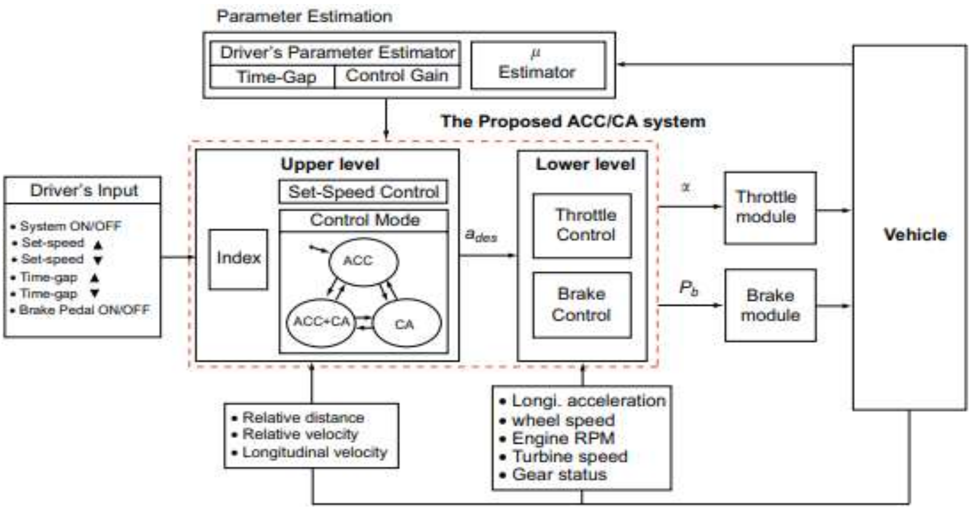

Figure 7. Scheme of ACC with CA

In order to design for $S_P(s) = \frac{1}{s}$ the controller, $R_P(s) = \frac{F(s)}{1-F(s)}\frac{1}{S_P(s)} = \frac{1}{\lambda}$ (dimensionless gain of the P controller). The nominee has a dimension of one second. The step disturbance change response is then approximately 4.5 sec, or 4.5 ms. In Figure 8 the velocity response is depicted. The host speed and vehicle distance exhibit the same acceleration response as in Figure 9. The proposed strategy achieve the zero steady state deviation for linear goal vehicle speed changes, as shown in (21), when the structure and parameters have the F(s) of the second order with the subsequent structure and parameters.

$$F(s) = \frac{1+s2\lambda}{1+s2\lambda+s^2\lambda^2} \qquad (21)$$

When the decay dynamics is again λ=1[s], then the system $S_P(s)$ controller with have the following structure shown in (22).

$$= \frac{1+s2\lambda}{s^2\lambda^2}\frac{s}{1}$$
$$=\frac{1+s\lambda}{s\lambda^2} \tag{22}$$

Figures 8 to13 shows that for all uncertain circumstances, the MRAC's performance is better than the nominal feedback controllers. As the value of the unknown parameter increases, the performance degrades Table 1 gives the comparison of acceleration of human and ACC method. MRAC nevertheless achieves good results even while the nominal controller's performance deteriorates and even oscillates.

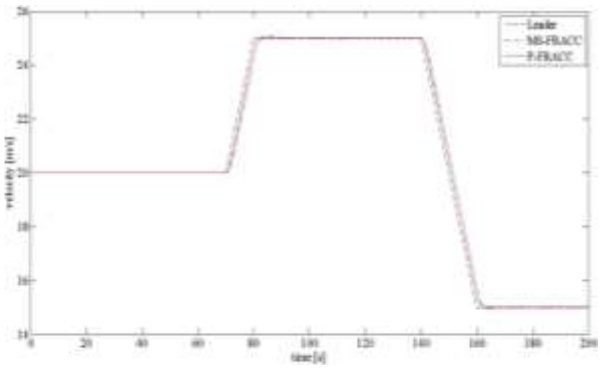

Figure 8. Velocity profile for ACC system under normal condition

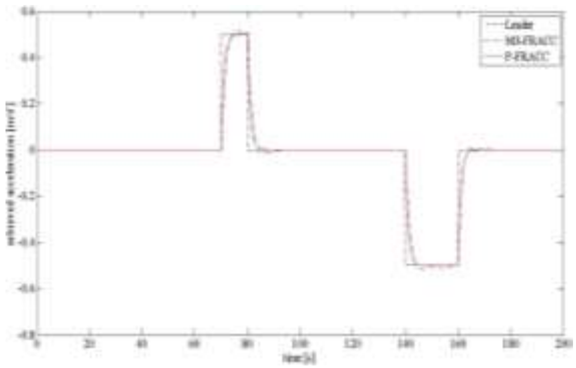

Figure 9. Acceleration profile for acc system under normal condition

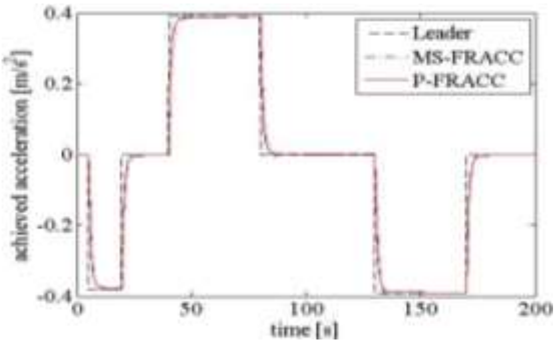

Figure 10. Velocity profile for ACC system under Stop and Go condition

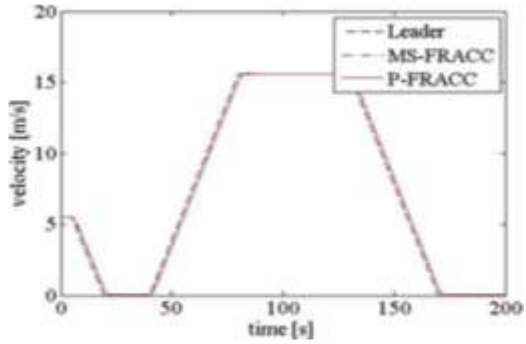

Figure 11. Acceleration profile for ACC system under stop and go condition

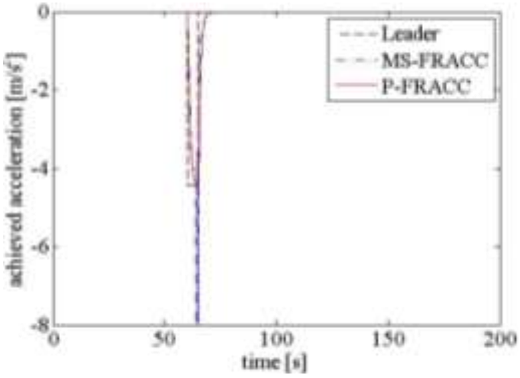

Figure 12. Velocity profile for ACC system under emergency condition

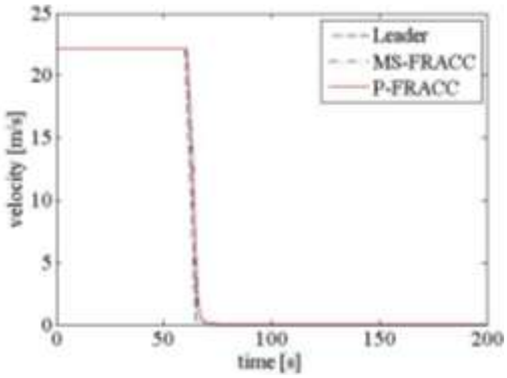

Figure 13. Acceleration profile under emergency condition

Table 1. Comparison of acceleration characteristics with ACC and human

	Acceleration (m/sec^2)		
	Preceding	Human	ACC
95%	1.89	1.31	2.02
75%	1.56	1.13	1.38
Mean	1.28	0.95	1.11
25%	1.03	0.83	0.79
5%	0.52	0.4	0.43
Variance	0.17	0.07	0.22

6. CONCLUSION

In order to achieve behavior of the subject vehicle that would appear natural to a human driver in typical driving scenarios and to achieve safe behavior in severe-braking situations when significant decelerations are required, the suggested learning-based (GA with Reinforcement algorithm) ACC with CA control algorithm was created. The recommended algorithm operates the subject car in three distinct modes to combine the ACC and CA systems. The goal of "comfort-mode" (control mode-1) is to keep a safe gap between the vehicles in front of it while giving the driver the appearance that they are doing it naturally. On a test car, the ACC/CA system was also put into use. In both high-speed driving and low-speed SG circumstances, it has been demonstrated that the suggested control system can generate a natural following performance that is comparable to human manual driving. Additionally, it can stop dangerously close vehicle-to-vehicle distances from developing as a result of hard braking circumstances. Driver acceptance of an integrated, full-range ACC/CA system can be successfully increased with the help of the vehicle longitudinal-control algorithm proposed in this study. A novel method of learning algorithm-based modelling will eventually aid the ACC system in bringing about a paradigm shift in the automotive sector.

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