September 23 (Tue.) 12:40-14:20

Room B

TuB1 Direct Yaw-Moment Control

Chair: Bo-Chiuan Chen (National Taipei University)

TuB1-1 Direct Yaw Moment Control and Power Consumption of In-Wheel Motor Vehicle

Takao Kobayashi[1], Etsuo Katsuyama[2], Hideki Sugiura[1], Eiichi Ono[1], Masaki Yamamoto[2]
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While direct yaw moment control significantly enhances vehicle dynamic performance, the additional power required to control vehicle motion still remains to be clarified. This paper constructed formulae for the mechanism by which direct yaw moment alters the cornering resistance and mechanical power of all wheels based on a simple bicycle model, including the electric loss of the motors and the inverters. These formulation results were validated by an actual test vehicle in steady state cornering. The validated theory was also applied to a comparison with several different driving force distribution mechanisms in terms of innate mechanical power.

TuB1-2 Driving Stability during Recuperation for Increased Rear Axle Loads with and without Torque Vectoring

Stephan Kaspar[1], Ralf Stroph[1], Alfred Pruckner[1], Sören Hohmann[2]
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Ongoing electrification of vehicles can lead to a space-saving drive train layout with two electric motors attached to the rear wheels and the battery placed in between. The resulting unconventional high rear axle load can result in stability problems and oversteer driving behaviour, especially during turning maneuvers. On the other hand, the single wheel drives can be used to stabilize the vehicle. This contribution investigates the influence of heavy rear axle loads in combination with and without torque vectoring on the recuperation potential during braking while cornering. Results are obtained by simulations as well as through real vehicle tests.

TuB1-3 Comparison of Deceleration Control and Yaw-moment Control Applied in the Early Stage of Cornering

Makoto Yamakado[1], Keiichiro Nagatsuka[2], Junya Takahashi[3]
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A yaw-moment control method for the cornering which generates enhancing moment in accordance with vehicle lateral jerk was compared with deceleration control based on G-Vectoring method. The analytic approach using the particle model clarified that the deceleration control is effective to reduce the magnitude of centrifugal force and make the instantaneous turning radius even small. The computer simulation results of L turn maneuver indicated that the instantaneous turning center of deceleration control was kept near side compared with moment control with small deceleration, and without control. This shows the advantage of the deceleration control especially for emergency case.

TuB1-4 Yaw Moment Control Using Fuzzy Reinforcement Learning

Aliakbar Akbari, Masoud Goharimanesh
Ferdowsi University of Mashhad

In this paper we present a fuzzy reinforcement learning control approach that requires no previous knowledge about vehicle model characteristics. By means of simulations we show that the scheme can perform well under a variety of maneuver and road conditions and adapt its behavior accordingly without requiring any overly complicated operations. Rule based fuzzy systems have been extensively applied with success in this area due to their similarity to human perception and reasoning. The fuzzy rules are optimized by reinforcement learning algorithms. The output of this procedure is an optimal policy which controls the vehicle dynamic stability.

Yaw Moment Control Using Fuzzy Reinforcement Learning

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In this paper we present a fuzzy reinforcement learning control approach that requires no previous knowledge about vehicle model characteristics. By means of simulations we show that the scheme can perform well under a variety of maneuver and road conditions and adapt its behavior accordingly without requiring any overly complicated operations. Rule based fuzzy systems have been extensively applied with success in this area due to their similarity to human perception and reasoning. The fuzzy rules are optimized by reinforcement learning algorithms. The output of this procedure is an optimal policy which controls the vehicle dynamic stability.

Vehicle dynamics, Autonomous driving, intelligent transportation systems

1. INTRODUCTION

One of the most important techniques to enhance the stability for the vehicle is the direct yaw moment control. This method was introduced by Shibahata et al. [1] in 1993. They devised this technique and presented that the direct yaw-moment control would provide the vehicle stability. The industrial version of this survey, was claimed by Zanten et al. [2] in 1994. They showed that, the differential braking forces would produce the required yaw moment to stabilize the vehicle in an abrupt maneuver. A pioneering research work dealing with this subject from different perspectives has been carried out so far.

Abe et al. [3] in 1996 applied DYC in a four wheel steer vehicle. Kano et al. in following year, 1997, used DYC for improving the semi-trailer braking performance [4]. In the same year, Nagai et al. integrated the DYC into active rear wheel steering to make a robust chassis system [5]. Abe in 1999, examined the four wheel steering and the direct yaw moment control all together [6]. In the same year, Nishimaki et al. proved the sliding mode theory for the yaw moment control [7]. Shino and Nagai, in 2001, presented the application of DYC in an electric vehicle [8]. In the same year, Esmailzadeh et al. developed the optimal control theory for this method [9]. Following this, they considered a bicycle model and derived the optimal gains analytically. Designing the fuzzy logic controller for DYC was conducted by Tahami et al. [10] in 2004. Boada, in 2005, presented the effect of the yaw moment control exposing to the cross wind [11]. Canale et al. in 2007, announced an active differential to produce the required moment for DYC [12]. Ding and Taheri in 2010, integrated the active front steering into DYC so as to enhance the vehicle stability. Moreover, they mentioned to the Lyapunov method in this case [13]. In the same year, Hu et al. [14] and Liu et al. [15] considered H2-H∞ and fuzzy-PID controller to design of DYC, respectively. Moreover, Robust controller like QFT was employed to enhance the dynamic stability in face of vehicle uncertainties[16].

Fuzzy inference systems offer robustness and smooth response. However they do involve the existence of an expert to define the suitable rule-set[17]. The main challenge is therefore to be able to make the appropriate rule-set without the existence of a direct trainer. Reinforcement learning can be practical in this situation to drive the generation of the suitable rule-set based on the interactions with the environment. It can also be simply combined with fuzzy logic and provide the relationship between the states and the accessible actions, which is the same as creating the fuzzy logic "if…then" engine[18].

The rest of the paper is organized as follows. In section 2, vehicle dynamics model is reviewed. Section 3, discusses more about fuzzy and reinforcement learning. In section 4, the simulations and results are considered and section 5 concluded the paper.

2. Vehicle Dynamics Model

A nonlinear 3DOF model considered for simulation purposes [19, 20]. Figure 1 illustrates the overall layout.

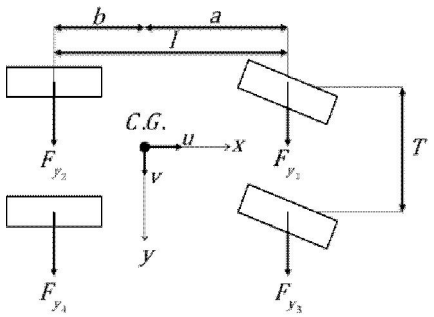


Fig. 1 Vehicle Model

Lateral, yaw and roll dynamics are formulated in 1-3.

$$F_{yfR}+F_{yfL}+F_{yrR}+F_{yrL}=m\left(\dot{v}+ur\right)+m_s h'\ddot{\varphi} \quad (1)$$

$$a\left(F_{yfR}+F_{yfL}\right)-b\left(F_{yrR}+F_{yrL}\right)=I_z\dot{r} \quad (2)$$

$$-m_s h'\left(\dot{v}+ur\right)-m_s h'\ddot{\varphi}-K_t\varphi+m_s gh'\varphi-C_t\dot{\varphi}=I_x\ddot{\varphi} \quad (3)$$

Where F_y shows the lateral force for the each tire. Front and rear tire is addressed by f and r .The right and left tire is presented by capital letters, R and L . In these equations, m_s is the sprungmass. h' is the distance between the center of gravity and the roll center. Roll angle is introduced by φ and the suspension stiffness and damping is presented by K_t and C_t respectively. In order to simulate the nonlinear regimes of the vehicle motion, the Magic Formula tire model with lateral slip is employed due to the capability of model to simulate the limit handling situations where strong nonlinearities are present [21]. The tire forces can be expressed as:

$$\left[F_{wxi}\ ,F_{wyi}\ ,M_{zi}\right]=f\left(\lambda_i,\alpha_i,\gamma_i,F_{zi}\right) \quad (4)$$

Where f is a non-linear function of the tire longitudinal slip λ_i , tire side slip angle α_i , camber angle γ_i ,and vertical load F_{zi} .

Table 1 Parameter Values

body sprung mass	m_s	6360 kg
body unsprung mass	m_{us}	500 kg
body roll moment of inertia	I_x	7695.6 kgm2
body yaw moment of inertia	I_z	30782.4 kgm2
track width	T	2.03 m
height of C.G.	H	1.2 m
Road friction	μ	0.9

To have a comprehensive model which is near to real vehicle, TRUCKSIM model is employed. Vehicle Parameters are listed in table1. Figure 2 shows the picture of vehicle used.

Fig. 2 Bus Picture in Trucksim

3. Fuzzy- Reinforcement Learning Strategy

Learning is a powerful tool for finding the optimum policy for a process. RL uses the environment feedback and make a signal named reinforcement. This signal may be reward or punishment. Agent is same as process and action is as controller signal. RL tries to find the best action for each state which agent (process) wants to move. Q-Learning is a simple algorithm which is used. This algorithm has a lookup table named Q table. It tries to estimate the discounted future rewards for taking actions from given states.
Algorithm 1 and table 2 demonstrate the detail of this algorithm.

Alg.1 Reinforcement Learning Principals[22]

Initialize Q(s,a) arbitrarily

Repeat for each episode:

- *Initialize s*
- *Repeat for each time step:*

  Choose a from s using policy derived from Q(s,a) (e.g., epsilon-greedy)
- *Take action a, observe r,s'*
- $Q\left(s_t,a_t\right)\leftarrow Q\left(s_t,a_t\right)+\alpha_t\left(s_t,a_t\right)\times\left[R_{t+1}+\gamma\times\max Q\left(s_{t+1},a_{t+1}\right)-Q\left(s_t,a_t\right)\right]$

  $s\leftarrow s'$
- *Until s is terminal*

TABLE 2 QLEARNING Terms definition

$Q\left(s_t,a_t\right)$	Old value
$\alpha_t\left(s_t,a_t\right)$	Learning rate
R_{t+1}	Reward
γ	Discount factor
$\max Q\left(s_{t+1},a_{t+1}\right)$	Maximum of future value
$R_{t+1}+\gamma\times\max Q\left(s_{t+1},a_{t+1}\right)$	Learned value

This method is either impracticable in case of large state- actions space, or impossible with continuous state space[23]. Many authors offered the methods for approximating the Q table. These methods cause to have slow solution. Another approach is to use fuzzy sets and reinforcement learning together. In this case all of states are like the inputs of fuzzy and action is defined as the output. Algorithm 2, discusses the Q-Learning reinforcement learning principals with their equations. N this method, Takagi-Sugeno FIS is used and all of rules are between input membership functions and the constant outputs are tuned by Q-Learning[23].

Alg.2 Q-Learning Reinforcement Learning[23] Principals

- *Observe the state x*
- *For each rule: choose the actual consequence using greedy or epsilon-greedy*
- *Compute the global consequence a(x) and its corresponding Q-value Q(x,a) by EQ. (5)*
- *Apply the action a(x) by EQ.(4) . Let y be the new state*
- *Receive the reinforcement r*
- *Update Q-values by EQ.(8)*

$$a(x)=\frac{\sum_{i=1}^{N}\alpha_i(x)\times a_i}{\sum_{i=1}^{N}\alpha_i(x)} \tag{4}$$

$$Q(x,a)=\frac{\sum_{i=1}^{N}\alpha_i(x)\times q\left[i.i^{\dagger}\right]}{\sum_{i=1}^{N}\alpha_i(x)} \tag{5}$$

$$V(x)=\frac{\sum_{i=1}^{N}\alpha_i(x)\times q\left[i.i^{*}\right]}{\sum_{i=1}^{N}\alpha_i(x)} \tag{6}$$

$$\Delta Q=r+\gamma V(y)-Q(x,a) \tag{7}$$

$$\Delta q\left[i.i^{\dagger}\right]=\alpha\Delta Q\frac{\alpha_i(x)}{\sum_{i=1}^{N}\alpha_i(x)} \tag{8}$$

In these relations, α is learning rate and α_i is truth value. Desired yaw rate and output yaw rate as the membership functions are considered in figures 3-4. The relationship with these membership functions and output is produced by reinforcement learning. Overall 81 states and 11 actions are considered.

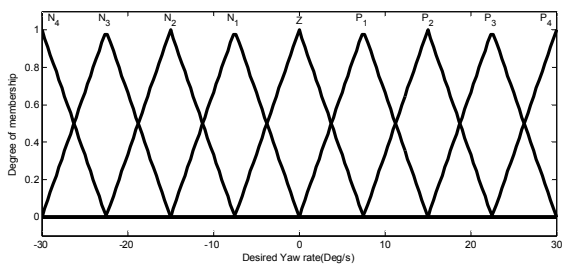


Fig. 3 Desired Yaw rate membership function

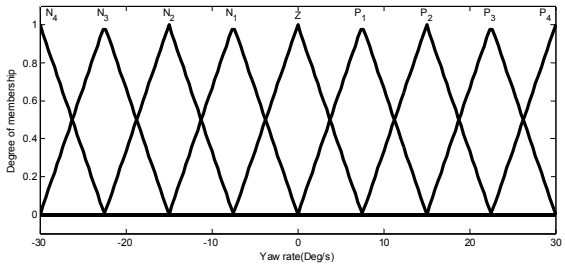


Fig. 4 Yaw rate membership function

In this paper action is the magnitude of yaw moment produced by differential braking. Q-learning a powerful RL algorithm is employed and with the definition of reward function, a policy is produced during learning procedure.

Rewards Function is determined as 9 where r and r_d are the output yaw rate and desired yaw rate. Also Roll angle is marked by Roll.

$$\mathrm{R}=\begin{cases}-100 & |r-r_d|>10\\ 0 & |r-r_d|\le 10\\ 100 & |r-r_d|\le 5\\ 1000 & |r-r_d|\le 2\\ 10000 & |r-r_d|\le 1\\ 100000 & |r-r_d|\le 0.5\\ -100 & |Roll|>5\\ -1000 & |Roll|>8\\ -1000000 & |Roll|>10\end{cases} \tag{9}$$

4. Simulation and results

To examine the controller policy, fish hook maneuver is employed to show the output yaw rate and position of vehicle before and after implementation of DYC. The steer angle is demonstrated in figure 5.

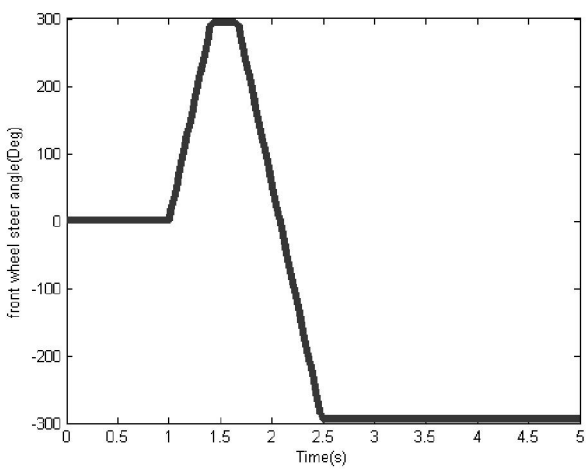


Fig. 5 Steer wheel angle

After learning of fuzzy rules by Q-learning with the proper parameters, the controller can control the yaw rate, Figure 6. Also the controller avoids rollover as shown in figure 7.

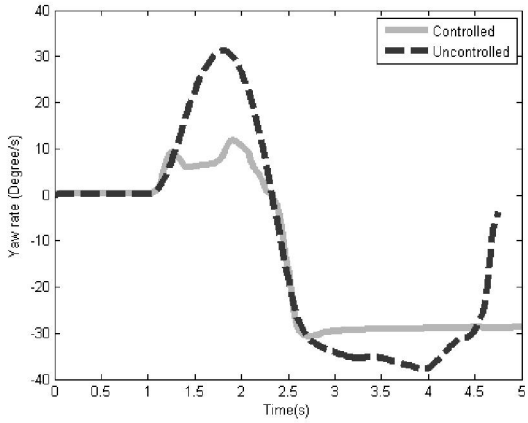


Fig. 6 Yaw rate

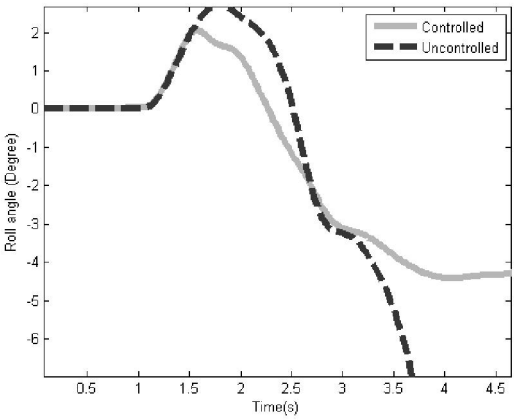


Fig. 7 Roll angle

Lateral acceleration is an important factor for a controlled vehicle. As figure 8 shows, controlled vehicle has a minimum lateral acceleration.

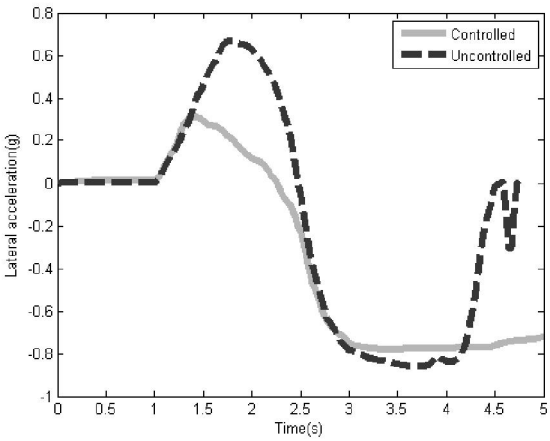


Fig. 8 Lateral acceleration

When vehicle is not controlled by a proper yaw moment, the longitudinal speed decreases dramatically. As figure 9 shows the controller could avoid this changing.

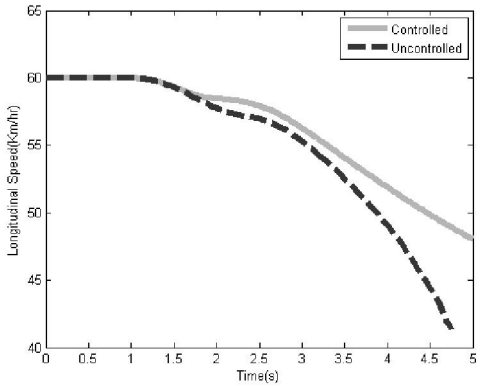


Fig. 9 Longitudinal speed

The global x-y position for fish-hook maneuver is depicted in figure 10 for controlled and uncontrolled vehicle.

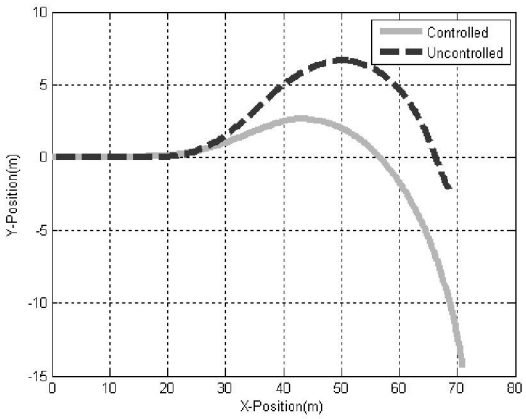
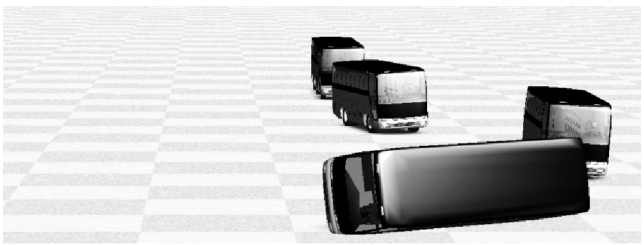


Fig. 10 Global X-Y Position

A. Controlled Vehicle



B. Uncontrolled Vehicle

Fig. 11. Vehicle maneuver animation

Figure 11, shows the graphical motion of bus in trucksim before and after implementing controller. The optimum policy made by fuzzy-RL is shown in figure 12.

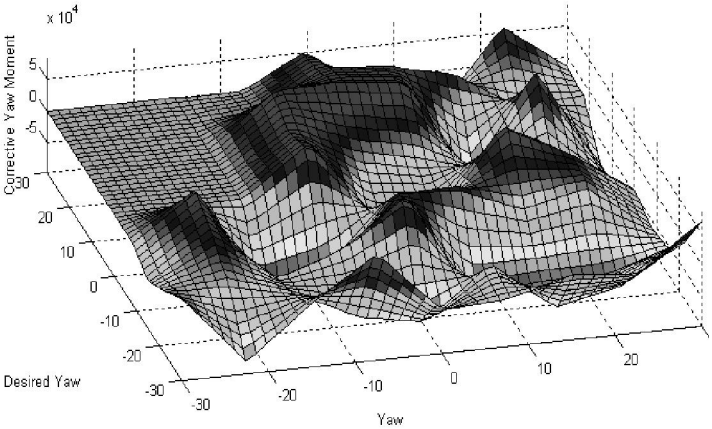


Fig. 12 Policy Surface

9. CONCLUSION

In this paper yaw moment controller is designing by fuzzy- Reinforcement learning algorithm. Fuzzy logic is not practical when the rules are determined without an expert. Using Q-learning, one of the powerful RL algorithm, we could recognize the optimal sets of rules for a Taskagi-Sugeno FIS. The results show the stability of vehicle could be enhanced.

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