

Path Tracking on Autonomous Vehicle for Severe Maneuvre

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Abstract

Autonomous vehicle consists self-learning process consists recognizing environment, real time localization, path planning and motion tracking control. Path tracking is an important aspect on autonomous vehicle. The main purpose path tracking is the autonomous vehicle have an ability to follow the predefined path with zero steady state error. The non-linearity of the vehicle dynamic cause some difficulties in path tracking problems. This paper proposes a path tracking control for autonomous vehicle. The controller consists of a relationship between lateral error, longitudinal velocity, the heading error and the reference yaw rate. In addition, the yaw rate controller developed based on the vehicle and tyre model. The effectiveness of the proposed controller is demonstrated by a simulation.

Keywords: Path tracking, Vehicle dynamic, Autonomous vehicle, Lateral error, Stanley controller

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1. Introduction

Intelligent vehicles played an important role in the development of intelligent transport systems that were being developed in recent years. Many research and industry institutions have conducted research on intelligent vehicles. Some of the latest vehicles have also been equipped with some intelligent devices that have been developed earlier. For example, the antilock braking system (ABS), electronic stability program (ESP), traction control system (TCS), electric power steering (ESS), electronic braking system (EBS), and automatic braking system (ABS) [1]. There are also several new technologies developed to support the realization of automatic driving. These new technologies that can be founded include adaptive cruise control system (ACC), automatic parking system (APS), anti-collision system (ACS) and advanced driver assistance system (ADAS).

Automatic driving is a complicated process that requires a self-learning process including environmental recognition, real time localization, path planning and motion tracking control. Some control strategies for this case can be found in many literatures such as the output feedback self-tuning controller proposed for lateral motion control of the vehicle [2]. Ref [3] provides an explanation for the use of the widely used H^∞ controller for path tracking based on the loop shape procedure for control. PID controller is a classical control algorithm used in various fields because it is easy to apply.

Ref [4] described that sliding mode controller is widely used in solving trajectory track problems. The fuzzy logic controller is also used for track tracking by using the skid steering vehicle method [5]. Also knowing the neural network controller used in vehicle steering and widely used in machine learning for nonlinear patterns. These methods implemented individually provide some shortcomings. Neural network requires both online and offline training and high computational cost that is associated to that training [6]. The combination of such methods in the control of the system is widely used in practical application, and the combination of methods gives better results [1].

Osman [7] presented cruise control performance of linear and non-linear systems using several control approaches including PID, state space and fuzzy logic. Development was then recorded for adaptive cruise control using machine learning approach. Technique called cooperative adaptive cruise control which aims to maintain the distance of the host vehicle to

another vehicle [8]. Hamid [9] proposed model predictive control combined with vehicle collision avoidance system that its performance compared to geometrical path tracking for collision avoidance provides significant results for several scenarios.

The researcher employed a feedback control to determine the vehicle's future position with respect to path and adjust the steering input to reduce the future error [10]. The control law consists of the heading error, lateral error and vehicle velocity, in a somewhat similar strategy as Stanley control law. The study is then enhanced in a later publication where spike detected to avoid erratic behaviour by controller due to GPS signal lost [11]. Ref [12] has reviewed several path tracking controllers based on geometrical approach that are widely used for autonomous vehicles.

However, many type of controller requires proper tuning to work efficiently. The adjustable controller can only work with certain types of trajectories, specific vehicle speed ranges and cannot perform on sharp cornering. The presences of the model uncertainties and external disturbances increase difficulties in path following control for autonomous vehicle. Model uncertainties may arise from the variations of the vehicle/environment parameters and the vehicle state. Contribution of the paper describes the application of the Stanley steering control law combined with vehicle dynamic control to extend the autonomous performance on severe manoeuvres such as sharp turns and adverse driving condition. Designed controller based on vehicle yaw rate is actively controlled to achieve trajectory tracking and adverse conditions.

2. Research Method

Dynamic and kinematic vehicle's behaviour modelling approaches can be used to do designing a lateral controller. The vehicle's weight, centre of gravity, cornering stiffness, wheel slippage and others were takes account into dynamic modelling. Equation of motion for kinematic and dynamic vehicle model for bicycle model show in (1-6) [13].

$$\dot{X} = v_x \cos \psi - v_y \sin \psi \quad (1)$$

$$\dot{Y} = v_x \sin \psi + v_y \cos \psi \quad (2)$$

$$\dot{\psi} = \dot{\psi} \quad (3)$$

$$\dot{v}_x = \frac{F_x}{m} + v_y \dot{\psi} \quad (4)$$

$$\dot{v}_y = \frac{F_y}{m} - v_x \dot{\psi} \quad (5)$$

$$\dot{\psi} = \frac{l_f F_{yf} - l_r F_{yr}}{I_z} \quad (6)$$

Looking at that equations, the main contributing external factor in this model is the tire forces which is the main source of external disturbance as well as the traction governing the vehicle motion. Tire forces arise from the deformation of the tire during different manoeuvring in both the longitudinal and lateral directions as the interaction between tire and road surfaces. Bicycle model and its kinematic and dynamic properties as shown in Figure 1.

If the wheel angle δ is small, the tire forces can be considered linear with the longitudinal and lateral slip angle. This linearization has been carried out on a full vehicle dynamic model and bicycle model. Linearization of lateral and longitudinal forces are shown respectively in equation [14].

$$F_y = C_y \alpha \quad (7)$$

Here C_x and C_y are defined as longitudinal and lateral cornering stiffness of the tire, s is the longitudinal slip angle and α is lateral slip angle. The equations for force and moments at the vehicle can be expressed as [13].

$$F_x = F_{xfl} \cos \delta_{fl} - F_{yfl} \sin \delta_{fl} + F_{xfr} \cos \delta_{fr} - F_{yfr} \sin \delta_{fr} + F_{xrl} \cos \delta_{rl} - F_{yrl} \sin \delta_{rl} + F_{xrr} \cos \delta_{rr} - F_{yrr} \sin \delta_{rr} \quad (8a)$$

$$F_y = F_{xfl} \sin \delta_{fl} + F_{yfl} \cos \delta_{fl} + F_{xfr} \sin \delta_{fr} + F_{yfr} \cos \delta_{fr} + F_{xrl} \sin \delta_{rl} + F_{yrl} \cos \delta_{rl} + F_{xrr} \sin \delta_{rr} + F_{yrr} \cos \delta_{rr} \quad (8b)$$

$$M_z = I_s (-F_{xfl} \cos \delta_{fl} + F_{yfl} \sin \delta_{fl} - F_{xfr} \cos \delta_{fr} + F_{yfr} \sin \delta_{fr}) + I_s (F_{xrl} \cos \delta_{rl} - F_{yrl} \sin \delta_{rl} + F_{xrr} \cos \delta_{rr} - F_{yrr} \sin \delta_{rr}) \\ + I_r (F_{xfl} \sin \delta_{fl} + F_{yfl} \cos \delta_{fl} + F_{xfr} \sin \delta_{fr} + F_{yfr} \cos \delta_{fr}) + I_r (-F_{xrl} \sin \delta_{rl} - F_{yrl} \cos \delta_{rl} - F_{xrr} \sin \delta_{rr} - F_{yrr} \cos \delta_{rr}) \quad (8c)$$

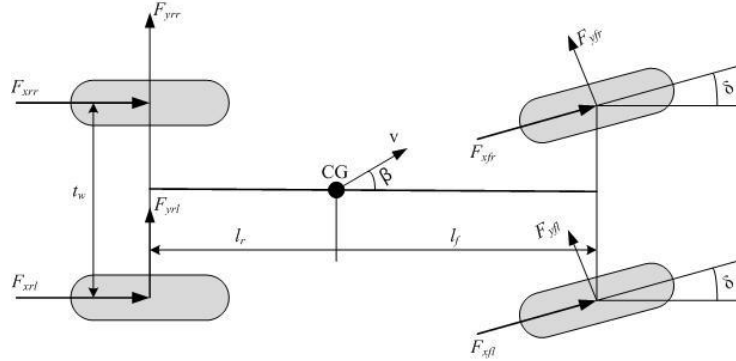


Figure 1. Bicycle model and its kinematic and dynamic properties

In that equations, δ_{**} is the steering angle of a given wheel, with the first subscript representing front/rear and second subscript right/left. The tires are very impact on the dynamics of the car because of the components that generate outside forces. Tire longitudinal forces, lateral force and aligning moment are complex nonlinear functions. These forces were as function of tire normal force, slip, slip angle and tire-road friction coefficient. The longitudinal tire slip is defined as [13].

$$s_j = \frac{\omega_{wyj} R_j - V_{xi}}{V_{xi}} = \frac{\omega_{wyj} R_j}{V_{xi}} - 1 \quad (9)$$

Where ω_{wyi} is wheel rotational speed along wheel Y axis, V_{xi} is the longitudinal speed, and R_i is the tire effective radius. The slip angle for each tire can be calculated as [13].

$$\alpha_{fl} = -\delta_{fl} + \tan^{-1} \frac{V_y + r_l f}{V_x - r_l s} \quad (10a)$$

$$\alpha_{fr} = -\delta_{fr} + \tan^{-1} \frac{V_y + r_l f}{V_x - r_l s} \quad (10b)$$

$$\alpha_{rl} = -\delta_{rl} + \tan^{-1} \frac{V_y - r_l f}{V_x - r_l s} \quad (10c)$$

$$\alpha_{rr} = -\delta_{rr} + \tan^{-1} \frac{V_y - r_l f}{V_x + r_l s} \quad (10d)$$

The normal forces on each tire can be calculated using the equation [13].

$$F_{zfl} = \frac{m_v g l_r}{2(l_f + l_r)} \quad (11a)$$

$$F_{zfr} = \frac{m_v g l_r}{2(l_f + l_r)} \quad (11b)$$

$$F_{zrl} = \frac{m_v g l_f}{2(l_f + l_r)} \quad (11c)$$

$$F_{zrr} = \frac{m_v g l_f}{2(l_f + l_r)} \quad (11d)$$

The main purpose in the path tracking control are provide sufficient steering input as well as throttle and braking input to control the direction and speed of the vehicle to guide the controlled vehicle along a predefined path. There are several type controllers for path tracking problems that are geometric, kinematic and dynamic. Geometric controller was most popular used in autonomous steering control due to its simplicity and stability. Stanley method was a geometric controller developed by Stanford University that won DARPA Grand Challenge in 2005.

The overall architecture of the vehicle was described by Thrun et al., (2006) [15] and steering control for path tracking controlled was detailed by Hoffman et al. (2007) [16]. In [17] showed a line tracking system for autonomous high speed vehicles. By adding the intersection location, this embedded system shows an accuracy of over 98% at 200km / hour. Ref [18] presents a concept of platoon movement of autonomous vehicles that vehicles have Adaptive or Advanced cruise control (ACC) system. Ref [19] presented the proposed autonomous mobile robot navigation scheme for several cases are designed and modeled in Simulink and MATLAB in unknown environment with obstacle avoidance is based on using fuzzy logic and wavelet network. The path tracking system employed a nonlinear geometric controller considering heading error and lateral error.

$$\delta(t) = \theta_e + \tan^{-1} \frac{k e_{fa}}{v} \quad (12)$$

Where θ_e the heading error between path direction and vehicle direction of motion, e_{fa} is the lateral error and v is the instantaneous velocity and k is the tuning gain of the vehicles as illustrated by Figure 2. The gain value of k is determined by the trial and error method. This method is performed to determine the best gain value k which gives the lowest RMSE value. The desired effect achieved with this control law as e_{fa} increases, the wheels are steered further towards the path.

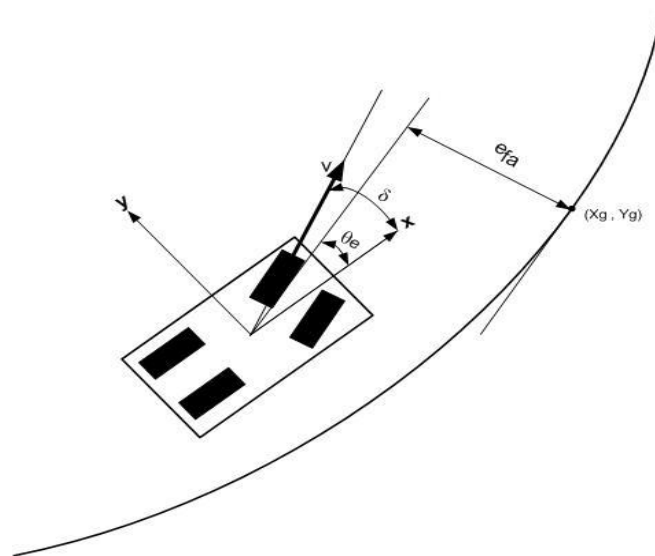


Figure 2. Stanley method geometry

The system control scheme used can be seen in Figure 3. The reference paths are x and y positions, then the path orientation is calculated. The error block calculates the error value of the lateral, longitudinal and orientation errors with the position input of the vehicle and the desired position. Furthermore, the results of calculations in the form of lateral error and orientation into the Stanley block controller to generate steering value. The yaw control block calculates the moment value with the desired yaw input with yaw generated by the vehicle model block.

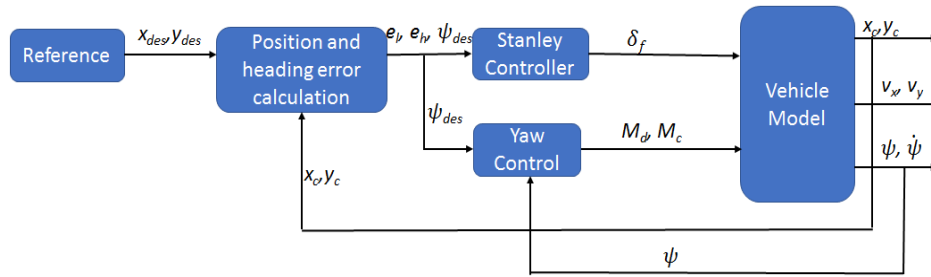


Figure 3. The control system model.

3. Results and Analysis

The development of the control system has been carried out for tracking of trajectories on autonomous vehicles. The development of the controller in this study used a vehicle model with 7 DOF. In addition to using kinematic and dynamical models of vehicles, tire models are also used which consider the slip on the wheel and moment on the wheel. Tire forces were longitudinal force, F_x , lateral force F_y , and tire self-aligning moment, M_z on each of the wheels. Table 1 is a vehicle parameter used in the simulation.

Table 1. Vehicle parameter for simulation

m (kg)	L (m)	$I_z(\text{kgm}^2)$	l_f	l_r	V(m/s)	Width (m)	C_{yf} (N/rad)	C_{yr} (N/rad)	R_i (m)
1350	2.78	13201	1.14	1.64	10,15,20	1.55	40200	62800	0.3

Proportional-differential controller is used to control the yaw rate and moment on the wheel. Figure 4 shows trajectory tracking result of the vehicle on global trajectories. The controller used gives significant results for path tracking with a maximum speed of 10 m/s (36 kph). The vehicle could follow the desired reference trajectory with sharp turning. Figure 6 shows a decrease in longitudinal speed at the start of a turn. A decrease in the longitudinal velocity is performed to adjust the curvature of the curve. For sharp turns as showed Figure 5 the lowest speed drops at 4.95 m/s. Heading error from the controller is also shown in Figure 5. The controller can track well the heading path, but when the autonomous vehicle starts to turn a heading error of 10 degrees. Then the heading error vehicle oscillates until finally the autonomous vehicle is stable again. This is seen by decreasing the heading error value until it reaches zero at 10 seconds.

The comparison between the desired yaw rate and the yaw rate generated by the controller can be seen in Figure 5. The controller still generates a substantial error even though the vehicle can still follow the desired path. This exists because the yaw rate generated by the controller is only based on the calculation of position error between the current position of the vehicle with the desired position.

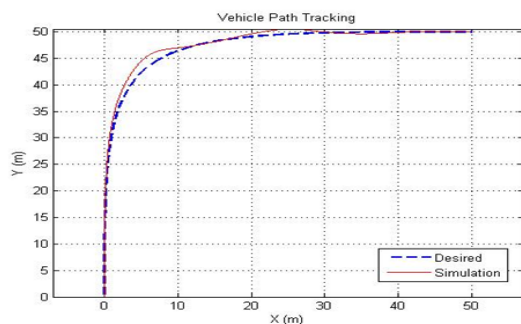


Figure 4 vehicle path tracking with 10 m/s vehicle speed, tuning gain 1

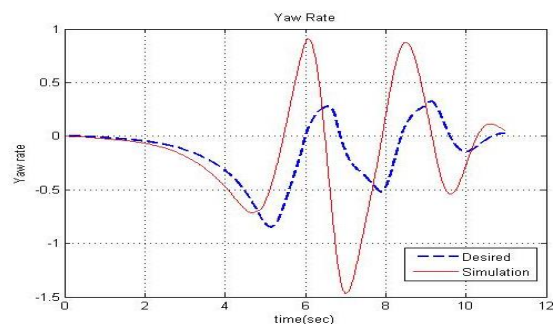


Figure 5 Yaw ratereponse of desired model

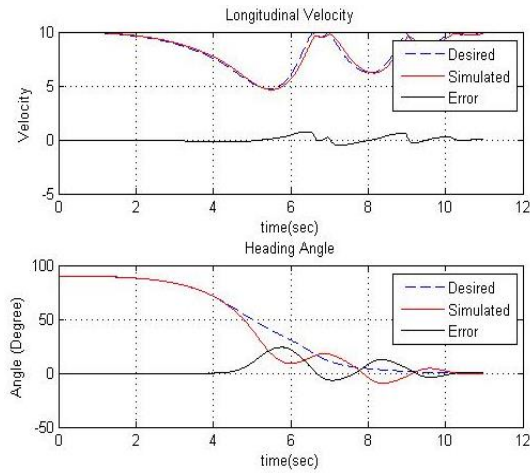


Figure 6. longitudinal and heading angle error for vehicle speed 10 m/s

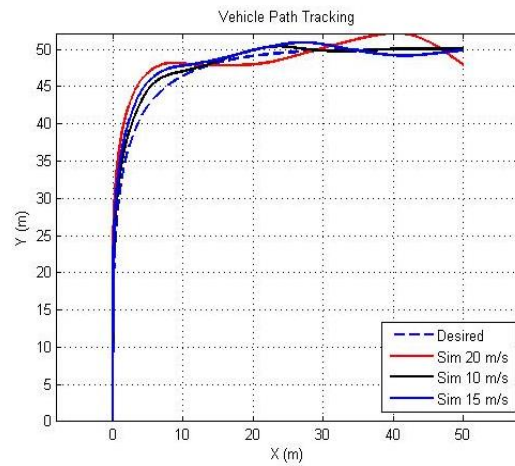


Figure 7. Path tracking response at different vehicle speed

Figure 7 is a comparative result of the simulation of paths simulation for several speeds of the vehicle. From Figure 7 can be seen that path tracking can be performed well for vehicle speed 10 m/s. The larger the vehicle speed the greater the lateral error generated by the controller. Larger lateral errors occur when the autonomous vehicle turns sharply.

Table 2 show three test with different speed 10 m/s, 15 m/s and 20 m/s. RMSE is the value root mean square error of the Stanley controller for that variation speed vehicle. Speed 20 m/s has the biggest error tracking that is 1.87. This suggests that tracking paths using a 20-vehicle speed have not produced good results. In this study, the Stanley controller gives the smallest error value when the velocity of 10 m/s is 0.75 m.

Table 2 Performance of Stanley controller with speed vehicle variation

Vehicle speed (m/s)	RSME
10	0.75
15	1.25
20	1.87

4. Conclusion

This paper describes a path tracking controller for autonomous vehicle. The controller designed based on yaw rate and interaction vehicle/tire dynamic model. A simple kinematic model can suffice when vehicle drive with slow speed. The simulation has been done for 10 m/s, 15 m/s and 20 m/s vehicle speed.

The simulation shows the good performance of the control tracking on desired trajectory for 10 m/s vehicle speed. At that speed, the tracking path controller can follow the desired path successfully. However, for vehicle speeds above 10 m/s, tracking path controller shows an increase in mean square error value. This occurs is due to the gain was tuned at the speeds of 10 m/s. For future work, this controller will be combined with an adaptive control approach to adapt the variations of speed to achieved desired trajectory.

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References

[1] G Han, W Fu, W Wang, Z Wu. The Lateral Tracking Control for the Intelligent Vehicle Based on Adaptive PID Neural Network. *Sensors*. 2017; 17(6): 1-15.

- [2] P Corke. Robotics, Vision and control. Second. Chennai, India: Springer. 2013.
- [3] I Sohnitz, K Schwarze. *Control of an Autonomous Vehicle: Design and First Practical Results*. Proceedings 199 IEEE/IEEJ/JSAI International Conference on Intelligent Transportation Systems. 1999; 4: 448-452.
- [4] J Yang, R Ma, Y Zhang, C Zhao. Sliding Mode Control for Trajectory Tracking of Intelligent Vehicle. *Physics Procedia*. 2012; 33: 1160-1167.
- [5] X Wang, M Fu, Y Yang, H Ma. Lateral Control of Autonomous Vehicles Based on Fuzzy Logic. *Control Engineering Practice*. 2015; 34: 1-17.
- [6] TC Martin, ME Orchard, PV Sánchez. Design and Simulation of Control Strategies for Trajectory Tracking in an Autonomous Ground Vehicle*. *IFAC Proc. Vol.* 2013; 46(24): 118-123.
- [7] K Osman, MF Rahmat, MA Ahmad. *Modelling and controller design for a cruise control system*. Proc. 2009 5th Int. Colloq. Signal Process. Its Appl. CSPA 2009; 1: 254-258.
- [8] C Desjardins, B Chaib-draa. Cooperative Adaptive Cruise Control: A Reinforcement Learning Approach. *IEEE Trans. Intell. Transp. Syst.* 2011; 12(4): 1248-1260.
- [9] Umar Zakir Ahmad Hamid, Mohd Hatta Mohammed Ariff, Hairi Zamzuri, Yuichi Saito, Muhammad Aizzat Zakaria, Mohd Azizi Abdul Rahman, Pongsathorn Raksincharoensak. Piecewise Trajectory Replanner for Highway Collision Avoidance Systems with Safe-Distance Based Threat Assessment Strategy and Nonlinear Model Predictive Control. *J. Intell. Robot. Syst. Theory Appl.*, 2017: 1-23.
- [10] MA Zakaria, H Zamzuri, SM Amri, SMHF Zainal. Vehicle Path Tracking Using Future Prediction Steering Control. *Eng. Procedia*, 2012; 41(5): 473-479.
- [11] MA Zakaria, H Zamzuri, R Mamat, SA Mazlan. A Path Tracking Algorithm Using Future Prediction Control with Spike Detection for an Autonomous Vehicle Robot. *Int. J. Adv. Robot. Syst.*, 2013; 10(309): 1-9.
- [12] N Hafizah, A Hairi, K Hudha, Z Abdul. Modelling and Control Strategies in Path Tracking Control for Autonomous Ground Vehicles: A Review of State of the Art and Challenges, *J. Intell. Robot Syst.*, 2017; 86: 225-254.
- [13] J Wang, J Steiber, B Surampudi. *Autonomous Ground Vehicle Control System for High-Speed and Safe Operation*. American Control Conference, 2008: 218-223.
- [14] L Li, F Wang. *Advanced Motion Control and Sensing for Intelligent Vehicle*, First. New York: Springer, 2007.
- [15] S Thrun *et al.* Stanley: The robot that won the DARPA Grand Challenge. *J. F. Robot.*, 2006; 23(9): 661-692.
- [16] GM Hoffmann, CJ Tomlin, D Montemerlo, S. Thrun. *Autonomous Automobile Trajectory Tracking for Off-Road Driving: Controller Design, Experimental Validation and Racing*. American Control Conference. 2007; 2296-2301.
- [17] Yahya Zare Khafri, Ali Jahanian. Improved Line Tracking System for Autonomous Navigation of High-Speed Vehicle. *International Journal of Robotics and Automation*. 2012; 1(3): 163-164.
- [18] Zoran Gacovski, Stojce Deskovski. Different Control Algorithms for a Platoon of Autonomous Vehicles. *International Journal of Robotics and Automation*. 2014; 3(3): 151-160.
- [19] Mustafa I Hamzah, Turki Y Abdall. Mobile Robot Navigation using Fuzzy Logic and Wavelet Network. *International Journal of Robotics and Automation*. 2014; 3(3): 191-200.