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Transportation Research Procedia 72 (2023) 3762–3768

Transportation Research Procedia

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Transport Research Arena (TRA) Conference

Real-time implementable intelligent trajectory controller design for a light commercial vehicle

Y. Mohamed[a], M. Gol[b], T. Kabbani[a], M. Ghazali[a], A. Demir[c], A. S. A. Sangani[1], K. Rodoplu[c], C. Derse[d], A. E. Hartavi[a,]*

[a]*MES Department, Center of Automotive Engineering, University of Surrey,Guildford, UK,*
[b]*Electric and Automation Department, Istanbul Gelisim University, Istanbul, TURKEY*
[c]*TOFAŞ Türk Otomotiv A.Ş., Bursa, TURKEY*
[d]*Oyak Renault Inc., Balat, Industry, Bursa, TURKEY*

Abstract

Light Commercial Vehicles (LCVs) are widely used for last-mile delivery of goods to manufacturers and consumers due to their ease of manoeuvrability, better mileage, and lower operating costs. They account for over 80% of total commercial vehicle sales in the European Union. Therefore, automation of LCVs has a significant socio-economic impact. A fuzzy trajectory controller with a minimum number of rules is designed for a hypothetical Level 3 autonomous vehicle (L3AV) and tested in a narrow road scenario. The analysis of the simulations showed that the maximum tracking error in the angular position was 4.1° at 4 m/s, 6.3° at 6 m/s, and 6.7° at 8 m/s, while the maximum lateral error was 0.1 m in all scenarios. The results have shown that the proposed controller achieves acceptable performance at different speeds with a minimum number of rules, leading to real-time implementation.

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Peer-review under responsibility of the scientific committee of the Transport Research Arena (TRA) Conference

Keywords: Trajectory Controller; Fuzzy Controller; Light Commercial Vehicle; Level 3 Autonomous Vehicle, Intelligent Control Strategy

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1. Introduction

Nonlinear real-time trajectory tracking techniques can be very computationally intensive (Li et al., 2016). In particular, trajectory tracking controllers for autonomous vehicles must cope with the nonlinear dynamics of the vehicle and other uncertainties (Calzolari et al., 2017). Therefore, researchers have developed intelligent techniques to reduce the computational cost of conventional nonlinear techniques some of which includes fuzzy logic and neural networks (Chain el. al., 2004, Cigánek, 2015, Lin and Lee, 1991). In the literature, various intelligent control

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* A. E. Hartavi. Tel.: +44 750 262 1216.
E-mail address: a.hartavikarci@surrey.ac.uk

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Peer-review under responsibility of the scientific committee of the Transport Research Arena (TRA) Conference
10.1016/j.trpro.2023.11.513

techniques were applied ranging from multi-layer neural networks to adaptive neuro-fuzzy inference systems. Nguyen and Widow (1990) developed a neural network controller for the truck backer upper to a loading dock from an arbitrary initial position by manipulating the steering. Garcia-Cerezo (1995) proposed a method for developing and tuning fuzzy path tracking algorithms for autonomous vehicles. In Hoffman (2001), the performance of a fuzzy controller is improved by tuning parameterized membership functions and input-output scaling factors using an evolutionary algorithm with respect to the desired control behavior. Bentalpa and Hajjaji (2002) focused on stabilizing fuzzy controllers for the trajectory tracking problem of a nonlinear vehicle model by solving the linear matrix inequality (LMI). Although the same technique is implemented, each study takes a slightly different approach than the other. Based on the implemented scenario, most of the parking scenarios used a multi-input multi-output (MIMO) approach for the fuzzy controllers (Nakrani and Joshi, 2018, Chang and Li, 2002). This approach provided accurate parking space measurements and precise control of the lateral and longitudinal dynamics. However, MIMO approaches for using a Fuzzy Inference System (FIS) proved less robust in high-speed scenarios. Therefore, decoupled fuzzy controllers control the throttle and steering of the vehicle, Hodge and Trabia (1999), Najanro (2007). This design allows the vehicle to respond robustly but increases the computational cost.

However, control techniques may not perform as expected under different operating conditions and manoeuvres. Therefore, the test scenarios must be carefully selected to ensure that the control technique performs well in challenging situations. In this paper, a real-time fuzzy logic controller was proposed to safely navigate a Level 3 autonomous van (SAE,2016) on a narrow road. The controller's capabilities lie in its: (i) simple structure, (ii) the low computational power required to navigate the vehicle among the parked cars and (iii) its fast response time.

The rest of the paper is organized as follows. Section 2 discusses the theory behind the use of the vehicle kinematic model. Section 3 describes the design of the fuzzy trajectory controller and the control structure. Section 4 shows the results of integrating the kinematic model and the FIS; applying it to a narrow road scenario (NRS). Finally, Section 5 summarizes and discusses the results of the paper using performance indicators.

2. Vehicle Model

In the literature, different techniques are used for vehicle modeling depending on the controller's requirements and the complexity of the chosen scenario. They range from a simple geometric method based on Ackerman steering (Dong et al. ,2000), to a kinematic model (Jummin et. al. ,2008 and Wit et. al.,2004), to a more complex but very realistic approach called a dynamic model (Allou, 2017, Kapania and Gerdes, 2015, Hajjaji, and S. Bentalba,2003). In this study, a kinematic vehicle model is used (Kong et al., 2015, Raffo et al., 2009, Rajamani 2012), which represents the two left tires as one front tire and the two rear tires as one rear tire, as shown in Fig. 1.

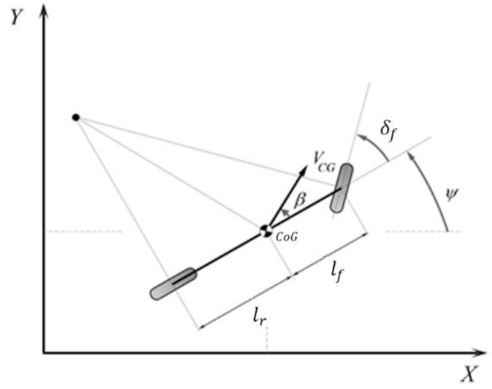


Fig. 1. Kinematic Model

The model describes the vehicle's movements with respect to the global X, Y coordinates and orientation angle of vehicle with respect to global X axes. In Fig. 1, the velocity of the center of gravity is shown as V, and it makes an angle β with the longitudinal axis, which is called the slip angle. The equation of motion is given as:

$$\dot{X}=V\cos(\psi+\beta) \tag{1}$$

$$\dot{Y}=V\sin(\psi+\beta) \tag{2}$$

$$\dot{\psi} = \frac{V\cos\beta}{l_f+l_r}\left(\tan\delta_f\right) \tag{3}$$

$$\beta = \tan^{-1}\frac{l_r\tan\delta_f}{l_f+l_r} \tag{4}$$

where l_f, l_r are the distances from the front and rear axles to the Center of Gravity (CoG), respectively, δ_f is the front wheel steering angle, ψ is the heading angle and $\dot{\psi}$ is the angular velocity of the vehicle. The MATLAB/Simulink model of the hypothetical vehicle was built based on the derived mathematical expressions (1-4).

3. Intelligent Trajectory Controller

In this section, a Mamdani-type fuzzy trajectory controller that has three variables, two inputs, and one output is presented. The two inputs of the controller are lateral and angular errors, while the output is defined by the steering angle, as shown in Fig. 2. Each variable has three linguistic variables that define its membership functions: Left, Null and Right. The "Null" is introduced as the value at which the tracking error can be tolerated.

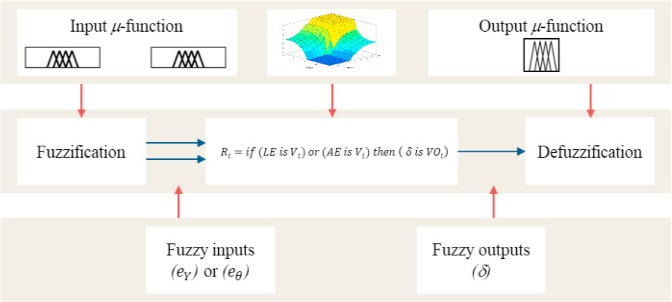


Fig. 2. Fuzzy logic controller inputs and outputs

As for the membership functions, the impulsive type of membership function was assigned. The decision to use trapezoidal and triangular membership functions is based on previous research that has shown that the use of linear triangular and trapezoidal functions increases the computational speed since they use less computationally intensive algorithms (Barua et. al., 2013 and Pedrycz, 1994). On the other hand, triangular membership functions are defined by only three value bounds: upper, lower and median. Fuzzy conditional statements of the controller can be expressed in the form:

$$R: if\ f(e_y\ is\ A_i)\ and\ f(e_\psi\ is\ B_i)\ then\ g(\delta_f\ is\ \xi_i) \tag{5}$$

where $i=1,2,\ldots n$ and n represent the number of rules, e_y is the lateral position error, and e_ψ, which is heading error, A_i, B_i are fuzzy sets consisting of triangular/trapezoidal membership functions representing the fuzzy subspace where the implication R can be applied for reasoning and δ_f represents the steering signal produced by the controller, while ξ is the steering angle produced to track the trajectory with minimum error.

The same linguistic variables were used for the controller output as for the inputs. The control signal is divided into right and left values, each of which also has small and large values, as shown in Fig. 3.

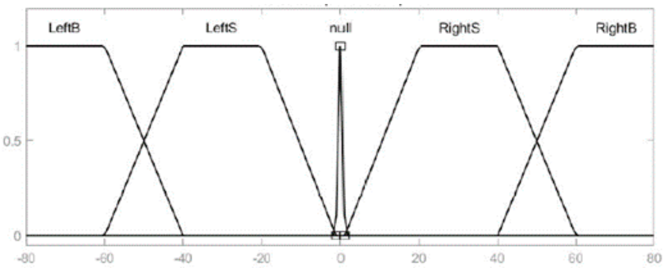


Fig. 3. Output membership function of the trajectory controller (LeftB: Left Big, LeftS: Left Small, RightB: Right Big, RightS: Right Small)

4. Simulation Model and Results

Driving in a changing environment without a driver is a complex dynamic control task and poses a real challenge. Therefore, these breakthrough technological products should be subjected to rigorous testing prior to deployment to address the safety and trust concerns of drivers and certifying bodies. Unfortunately, in the real world, there are an infinite number of possibilities that the system AD can encounter, and conducting tests for all possible scenarios on a test bench/test site requires both time and resources. This can only be achieved through scenario-based testing, which allows developers to design, configure, and visualise environments in which automated driving functions can be evaluated for almost all possible operating conditions, with/without hardware, without and without risk. The narrow road scenario was chosen because (i) it is a highly repetitive driving task for a delivery van in daily delivery operations and (ii) it is one of the most critical scenarios due to the relatively wide size of the vehicle. In this regard, a virtual environment that reflects the NR selected scenario was built in 16 actors, 5 buildings, 10 stationary vehicles, and the ego car using the MATLAB®/Scenario Designer tool shown in Fig. 4.

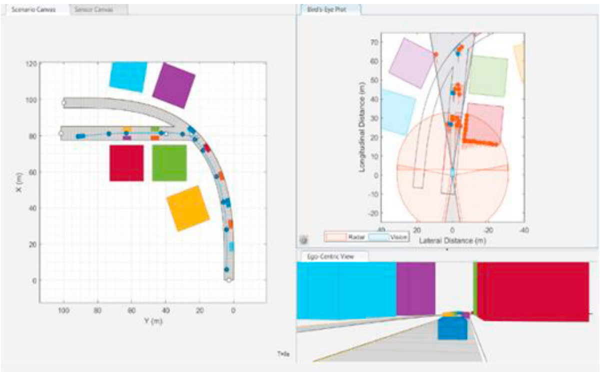


Fig. 4. Narrow road scenario in driver scenario designer tool

It was used to design synthetic driving scenario for testing tracking controller and to extract the data via its multimodal interface. Then the mathematical expressions of the vehicle (1)-(4) was integrated in MATLAB®/Simulink environment to model the vehicle. As a final step fuzzy trajectory controller was developed and integrated into the overall simulation model together with performance indicators used in the evaluation process.

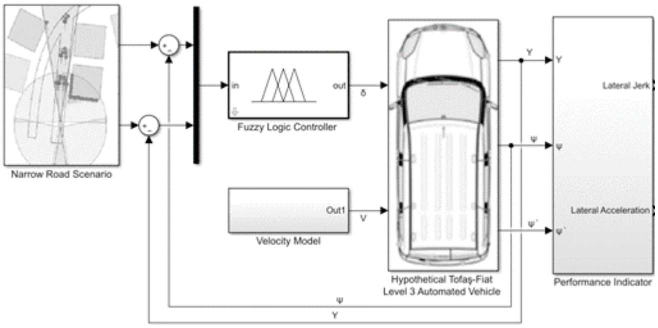
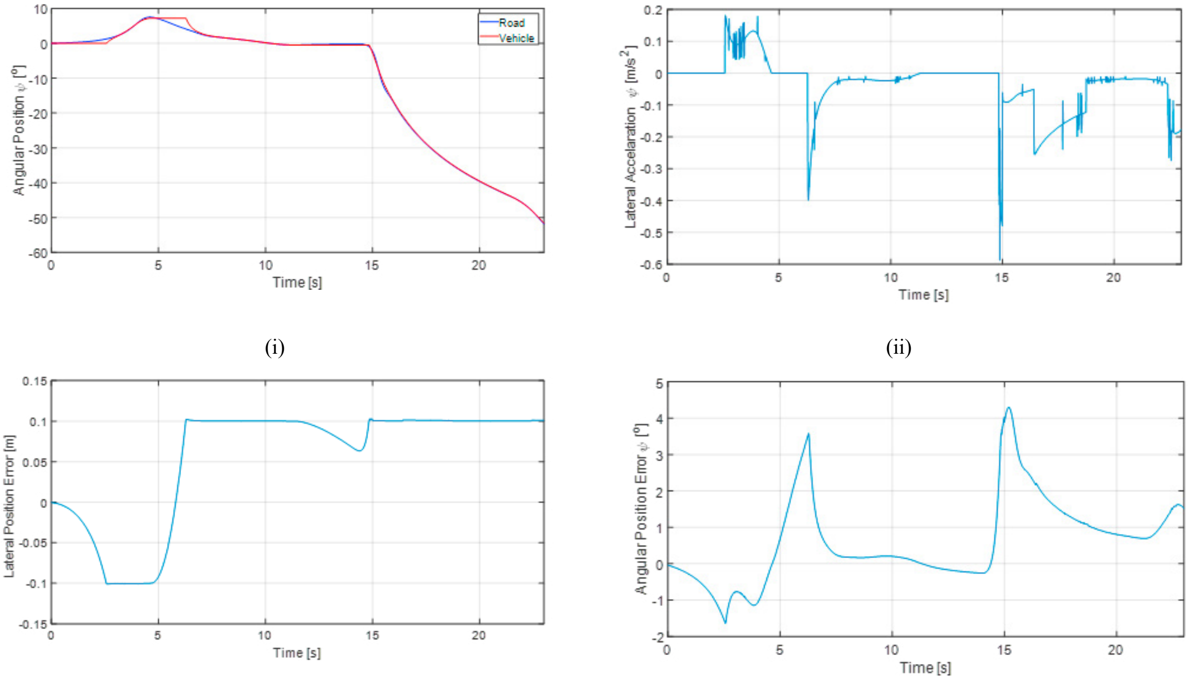


Fig. 5. MATLAB/Simulation model of the Tofas Fiat Hypothetical Level 3 Vehicle

The angular and lateral positions are critical to the behavior of the controller because they enable the assessment of the actual position of the vehicle with respect to reference. Furthermore, the control signal and lateral acceleration show the exact output of the controller, so they reveal any unexpected behavior of the controller. The lateral jerk shows the rate of change of acceleration due to the driver's cornering maneuver, which indicates the comfort of the vehicle, (Eager et. al., 2016). The threshold for comfort in lateral acceleration and jerk was found to be ±2 and ±0.9, respectively. Figure 6 shows the angular position, lateral acceleration, lateral position error, and angular position error with respect to time. According to the results, the maximum angular position error is 4.1° at 4 m/s, while the maximum lateral error is 0.1 m and the lateral acceleration is within the comfort zone.

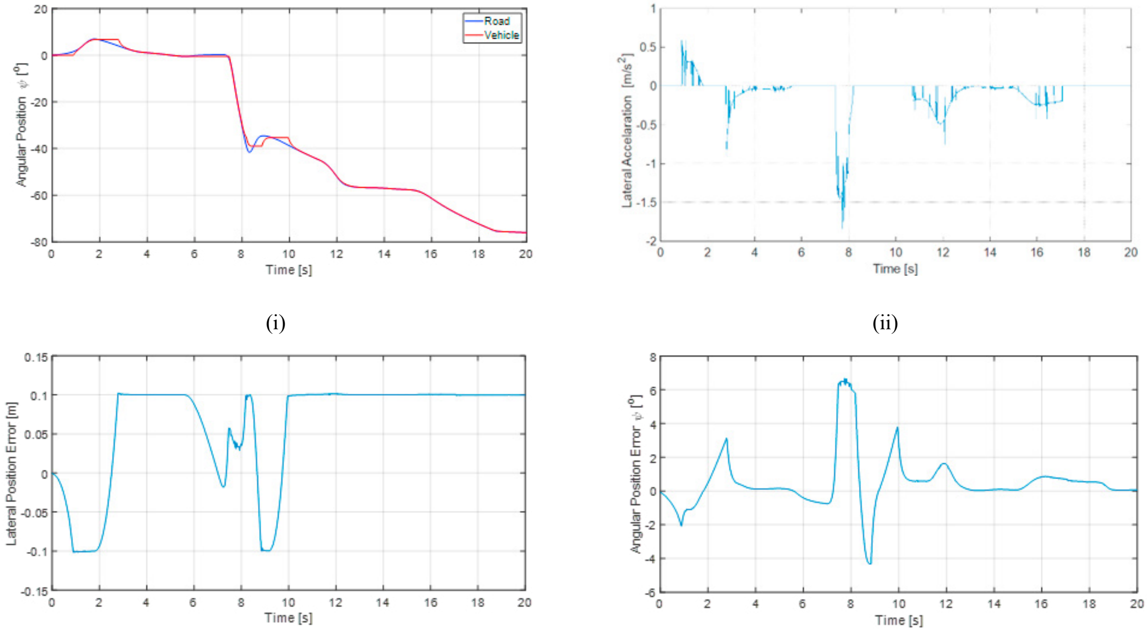


(i) (ii)

(iii) (iv)

Fig. 6. Narrow road scenario with a vehicle speed of 4m/s: i) Angular position, ii) Lateral acceleration, iii) Lateral position error, and iv) Angular position error with respect to time

Figure 7 shows the results for the 6m/s. Accordingly the maximum angular position error for that scenario is 6.3° at 6 m/s, while the maximum lateral error is still 0.1 m and the lateral acceleration is within the comfort zone.



(i)

(ii)

(iii)

(iv)

Fig. 7. Narrow road scenario with a vehicle speed of 6m/s: i) Angular position, ii) Lateral acceleration, iii) Lateral position error, and iv) Angular position error with respect to time.

The controller showed the best response with the least number of oscillations and errors at 4 m/s. Therefore, it was expected that the lower the speed, the better the ride quality would be.

5. Conclusion

Light commercial vehicle account for over 80% of total commercial vehicle sales in the Europe. Therefore, automation of LCVs enables an increase in safety and a reduction in delivery times and costs, resulting in higher productivity and reliability for logistics companies. The analysis of the simulation results showed that the tracking errors in the control response were minimal. The maximum tracking error in the angular position was defined as 4.1° at 4 m/s, 6.3° at 6 m/s, and 6.7° at 8 m/s, with a maximum lateral error of 0.1 m in all scenarios. To sum up, this paper successfully demonstrated the design of a fuzzy trajectory controller with a minimum number of rules for a Level 3 van for a narrow road scenario, which is a highly repetitive driving task in daily delivery operations.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation program under Grant Agreement no. 723324.

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