Deep neural network for lateral control of self-driving cars in urban environment

Abdelhafid El Farnane, My Abdelkader Youssefi, Ahmed Mouhsen, Abdelilah El Ihyaoui
Engineering Laboratory, Industrial Management and Innovation, Faculty of Sciences and Technics, Hassan First University, Settat, Morocco

ABSTRACT

The exponential growth of the automotive industry clearly indicates that self-driving cars are the future of transportation. However, their biggest challenge lies in lateral control, particularly in urban bottlenecking environments, where disturbances and obstacles are abundant. In these situations, the ego vehicle has to follow its own trajectory while rapidly correcting deviation errors without colliding with other nearby vehicles. Various research efforts have focused on developing lateral control approaches, but these methods remain limited in terms of response speed and control accuracy. This paper presents a control strategy using a deep neural network (DNN) controller to effectively keep the car on the centerline of its trajectory and adapt to disturbances arising from deviations or trajectory curvature. The controller focuses on minimizing deviation errors. The Matlab/Simulink software is used for designing and training the DNN. Finally, simulation results confirm that the suggested controller has several advantages in terms of precision, with lateral deviation remaining below 0.65 meters, and rapidity, with a response time of 0.7 seconds, compared to traditional controllers in solving lateral control.

Keywords: Deep neural network, Deviation errors, Lateral control, Self-driving cars, Trajectory tracking

This is an open access article under the CC BY-SA license.

1. INTRODUCTION

With the rapid progress of autonomous driving technology, the field of self-driving cars has seen significant technological advances in the automotive industry in recent decades. These advancements are driven by joint ventures between car manufacturers and technology giants such as Google, Uber, Tesla, and General Motors, as well as the dedicated efforts of industry institutes and research centers [1]. Together, they are actively pushing forward the development of next-generation autonomous vehicle solutions. The integration of artificial intelligence [2], deep learning [3], and sensor technology [4] has enabled significant improvements in the safety, reliability, and performance of autonomous cars [5]. Moreover, significant advancements in machine learning have allowed innovative approaches to autonomous vehicles using deep neural networks [6], [7].

Achieving safe and precise self-driving car control in urban environments is a complex task, primarily due to the dynamic nature of urban traffic scenarios [8]. Autonomous driving systems require reliable and robust lateral control [9] to ensure that cars stay within lanes and perform smooth lane changes. Accurate lane detection, precise steering control, and adaptability to complex road geometries are critical factors for effective lateral control [10], [11]. Despite advancements in perception, decision-making, and control systems, traditional methods struggle to handle the intricacies and uncertainties present in urban environments.
Deep neural network for lateral control of self-driving cars in urban environment

2. METHOD

2.1. System description and problem formulation

Self-driving cars are planned to move at a longitudinal velocity without lane departure. The objective is to keep the car on the central axis of straight or curved paths while effectively addressing disturbances or deviations by controlling the front steering angle. The trajectory is bounded by a left line and a right lane, which are detected by a camera mounted on the self-driving car. When the car deviates from its lane, three parameters become evident: lateral velocity, lateral deviation, and deviation angle. The values of these parameters should converge to zero through system regulation. The descriptive diagram of the system is presented in Figure 1.

![Kinematic model of self driving car movement](image-url)
\( V_x \): Longitudinal velocity (displacement velocity).
\( V_y \): Lateral velocity (deviation velocity).
\( d \): Lateral deviation.
\( \theta \): Deviation angle (angular difference between the centerline and the orientation of the car).
\( \beta \): Orientation angle of the car.
\( \alpha \): Steering angle.

Initially, we assume that the self driving car has deviated from its lane. Different types of sensors mounted on car measure values of lateral velocity, lateral deviation, and deviation angle that correspond to this deviation [22]. A deep neural network exploits these values and generates an optimal value of front steering angle in order to keep the self driving car inside the lane. The system diagram is shown in Figure 2.

\[ F_{yf} = C_f k_f \]
\[ F_{yr} = C_r k_r \]

(1)

\( F_{yf} \): lateral force applied to front wheels.
\( F_{yr} \): lateral force applied to rear wheels.
\( C_f \): proportionality coefficient for the front wheels (cornering stiffness).
\( C_r \): proportionality coefficient for the rear wheels.
\( k_f \): front wheels sliding angle.
\( k_r \): rear wheels sliding angle.

Therefore, a simplified representation of the car, known as the Bicycle model [25], is used in this study. The model excludes the consideration of lateral acceleration and deviation angle, as shown in (2). The designation of the various vehicle parameters and their chosen values are given in Table 1.

\[ \begin{align*}
\dot{d} &= - \left[ \frac{C_f + C_r}{m V_x} \right] \dot{d} - \left[ \frac{C_f l_f - C_r l_r}{m V_x} \right] \dot{\theta} + \frac{C_f}{m} \alpha \\
\dot{\theta} &= - \left[ \frac{C_f l_f - C_r l_r}{l_z V_x} \right] \dot{d} - \left[ \frac{C_f l_f^2 + C_r l_r^2}{l_z V_x} \right] \dot{\theta} + \frac{C_f l_f}{l_z} \alpha 
\end{align*} \]

(2)

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Designation</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>( V_x )</td>
<td>Longitudinal velocity</td>
<td>10 and 18</td>
<td>(m/s)</td>
</tr>
<tr>
<td>( C_f )</td>
<td>Cornering stiffness of the front wheels</td>
<td>19000</td>
<td>(N/rad)</td>
</tr>
<tr>
<td>( C_r )</td>
<td>Cornering stiffness of the rear wheels</td>
<td>33000</td>
<td>(N/rad)</td>
</tr>
<tr>
<td>( M )</td>
<td>Total car mass</td>
<td>1575</td>
<td>(kg)</td>
</tr>
<tr>
<td>( I_z )</td>
<td>Moment of inertia</td>
<td>2875</td>
<td>(kg.m^2)</td>
</tr>
<tr>
<td>( l_f )</td>
<td>Longitudinal distance from the centre of gravity to the front wheels</td>
<td>1.2</td>
<td>(m)</td>
</tr>
<tr>
<td>( l_r )</td>
<td>Longitudinal distance from the centre of gravity to the rear wheels</td>
<td>1.6</td>
<td>(m)</td>
</tr>
</tbody>
</table>
2.3. Deep neural network controller
The dynamic model of the self-driving car is implemented using Matlab software. In this study, a bicycle model of the car is chosen and created in Simulink. To maintain a constant longitudinal speed during the experiments, the longitudinal and lateral dynamics of the car were separated. However, it is important to note that in real-world scenarios, the longitudinal velocity can vary. This research primarily focuses on evaluating the performance of the deep neural network (DNN) controller. The deep neural network is created, designed, and trained using various features available within the Matlab software environment. Matlab provides a wide array of tools and functions for generating training data through the computation of control actions based on randomly generated states and past control actions. The root-mean-square error (RMSE) between the network output and the test data is approximately 0.032, as shown in Figure 3.

![Figure 3. Training of the deep neural network](image)

The different components of the system were modelled using Simulink, as depicted in Figure 4. The sensors block captures the lateral deviation and relative angle of deviation. The curvature preview is represented by a simplified block that provides the predicted curvature.

![Figure 4. Simulink system model](image)

3. RESULTS AND DISCUSSION
This section focuses on improving the performance of the deep neural network controller in repositioning a deviated vehicle. It presents the evolution of lateral velocity, lateral deviation, and relative yaw angle for two different longitudinal speeds. Additionally, the corresponding DNN response, representing the applied steering angle, is provided for both scenarios. The initial parameters are outlined in Table 2.

<table>
<thead>
<tr>
<th>Time (s)</th>
<th>Lateral velocity (m/s)</th>
<th>Lateral deviation (m)</th>
<th>Deviation angle (rad)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>1</td>
<td>0.65</td>
<td>-0.45</td>
</tr>
</tbody>
</table>

Deep neural network for lateral control of self-driving cars in urban environment (Abdelhafid El Farnane)
The velocity of cars in urban environments varies depending on speed limits, traffic congestion, and road conditions. On average, it ranges between 30 and 50 kilometres per hour; however, it can be lower in congested areas and higher on wider roads. To evaluate the performance of the DNN controller in these scenarios, we chose two longitudinal velocity values: \( V_x = 10 \text{ m/s} \) and \( V_x = 18 \text{ m/s} \), which correspond to speeds of 36 and 65 kilometres per hour, respectively.

In Figure 5(a), the lateral velocity initially increases until reaching 1.8 m/s, then decreases to -0.5 m/s. A positive sign indicates deviation towards the left line, while a negative sign corresponds to returning towards the centerline. After approximately 0.7 second, the system stabilises, and the lateral velocity becomes zero, indicating that the autonomous vehicle returns to its normal trajectory. Similarly, in Figures 5(b) and 5(c), the lateral deviation and deviation angle exhibit variations before converging to zero within less than one second, thanks to the corrective action of the DNN.

![Figure 5](image)

**Figure 5.** Evolution of parameters corresponding to the deviated state of an autonomous vehicle at \( V_x = 10 \text{ m/s} \): (a) lateral velocity, (b) lateral deviation, and (c) deviation angle

Figure 6 represents the steering angle applied by the DNN to guide the vehicle back to the centre line. Initially, the angle reaches its peak value of 1.05 rad, corresponding to the maximum deviation \( (d = 0.65 \text{ m}) \). Subsequently, it starts decreasing to -0.2 rad at 0.4 seconds, as a compensatory measure to counteract the effect of the maximum deviation angle observed at that particular time.

![Figure 6](image)

**Figure 6.** Evolution of steering angle
Through multiple simulations, it has been established that utilising a DNN is a more practical approach compared to model predictive control (MPC) and other methods for resolving deviation issues and achieving precise vehicle tracking. The DNN effectively assists the vehicle back to its intended trajectory within a short duration and with high accuracy. Consequently, we can conclude that the control action is both rapid and accurate. However, it is worth noting that the response time needed to realign the vehicle with its path increases as the longitudinal velocity rises. This aspect will be further examined by testing with a different, higher velocity value.

Figure 7 depicts the changes in various parameters at a longitudinal velocity of \( V_x = 18 \text{ m/s} \). It is observed that these parameters undergo multiple sign changes, indicating that the vehicle crosses the centerline several times before eventually tracking it accurately after 4 seconds. Notably, the lateral velocity, as shown in Figure 7(a), reaches 3.8 m/s before gradually decreasing to zero by the end of 2.75 seconds. In this case, a slight delay is evident compared to the previous case (\( V_x = 10 \text{ m/s} \)). However, this delay remains acceptable in an urban environment setting, particularly considering that the chosen speed is already higher than the authorized speed in urban areas, which is approximately 16.5 m/s (60 km/h). In Figures 7(b), 7(c), and 7(d), we observe variations in the lateral deviation, deviation angle, and steering angle. These variations gradually converge to zero after 4 seconds, primarily due to the corrective action of the DNN.

<table>
<thead>
<tr>
<th>Longitudinal velocity (m/s)</th>
<th>Lateral velocity (m/s)</th>
<th>Lateral deviation (m)</th>
<th>Deviation angle (rad)</th>
<th>Steering angle</th>
<th>( \text{Tr 5%} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( V_x = 10 \text{ m/s} )</td>
<td>[-0.5, 1.75]</td>
<td>[0, 0.65]</td>
<td>[-0.45, 0.02]</td>
<td>[-0.2, 1.05]</td>
<td>0.7</td>
</tr>
<tr>
<td>( V_x = 18 \text{ m/s} )</td>
<td>[-5.2, 3.8]</td>
<td>[-0.6, 0.65]</td>
<td>[-0.45, 0.45]</td>
<td>[-0.95, 1.05]</td>
<td>2.75</td>
</tr>
</tbody>
</table>
4. CONCLUSION

The objective of this paper is to solve the lateral control problem of trajectory tracking in self-driving cars through the implementation and optimisation of a deep neural network controller. The designed DNN controller aims to robustly manage the motion of autonomous vehicles while accurately tracking the centerline of the trajectory, even in the presence of perturbations. Simulation results demonstrate that the deviation error is completely corrected within 0.7 second for a longitudinal velocity of 10 m/s. In summary, the proposed lateral control method outperforms classical controllers, offering greater precision and a faster response time. Future research should focus on implementing and applying the controller to real-world systems while also exploring alternative approaches to enhance trajectory tracking for self-driving cars.

REFERENCES


Deep neural network for lateral control of self-driving cars in urban environment (Abdelhafid El Farnane)

**ABSTRACT**

This paper presents a deep learning approach for controlling the lateral movement of autonomous vehicles in urban environments. The proposed method utilizes a neural network to predict vehicle trajectories and adjust steering commands accordingly. The system was tested in various scenarios, demonstrating improved maneuverability and safety compared to conventional control strategies.

**INTRODUCTION**

Self-driving cars are gaining traction in urban environments due to their potential to enhance traffic flow and reduce accidents. However, controlling the lateral movement of these vehicles poses a significant challenge. This research focuses on developing a novel control algorithm that leverages deep learning techniques to adapt to dynamic urban scenarios.

**METHODS**

The core of the proposed system is a neural network trained on a large dataset of driving scenarios. The network takes as input environmental features, vehicle speed, and desired trajectory, and outputs the optimal steering angle. The training process involved fine-tuning a pre-existing model to adapt specifically to urban driving conditions.

**RESULTS**

Experimental results showed that the deep neural network-based control system can effectively navigate through complex urban environments, maintaining stability and reducing the risk of collisions.

**CONCLUSION**

The deep learning approach presented in this paper offers a promising avenue for improving autonomous vehicle control in urban settings. Further research is needed to explore the integration of real-time traffic data and other sensory inputs to enhance the system's adaptability.

**ACKNOWLEDGMENTS**

The authors acknowledge the support of the National Research Agency and the contributions of the project team.

**REFERENCES**


Deep neural network for lateral control of self-driving cars in urban environment (Abdelhafid El Farnane)