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AI-Powered Predictive Control in Autonomous Vehicles

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Abstract: Autonomous driving (AD) is an innovative technology poised to transform the future of transportation. In addition to providing a chance for enhanced road safety by minimizing human mistakes, the implementation of autonomous driving will increase traffic efficiency by facilitating superior driving and stability in traffic flow, as powerful predictive analytics algorithms may be built. This research emphasizes that the dynamics of an autonomous vehicle (AV) interacting with human drivers is a weakly collective, open-system complex that is essentially temporal and representation-hierarchical. To address the problem of achieving AI-enabled autonomous driving, we created predictive planning that incorporates perceptual and learning modules for task-relevant scene comprehension in operational and tactical planning. The discussion regarding AI-enabled transportation effectively distinguishes between functional and realization levels while integrating them within system engineering. The dynamics visualization framework for AI-enabled AD systems may be easily adapted to other analogous systems and processes inside vast complex systems.

Keywords: *AI-Enabled Autonomous Driving, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM), Computer Science, Data Science,Vehicle, Vehicle Reliability*

Introduction

Formulating planning and control algorithms for Autonomous Vehicles (AVs) in off-road settings is arduous owing to the unpredictable and unstructured nature of the environment, compounded with restricted sensor range capabilities resulting from occlusions. Unlike the controlled urban environment where autonomous cars adhere to traffic regulations, off-road scenarios include dynamic impediments such as adjacent vehicles that navigate erratically and without legal constraints, complicating safe AV navigation. Suboptimal performance and safety issues stem from the rigidity of conventional autonomous vehicle planning heuristic methods such as A*, Dijkstra, RRT, RRT*, and D* [3]-[5]. Advanced tactics are required to foresee and overcome these problems.

AI models based on situational intelligence have tackled the issues of safe planning and control for autonomous vehicles. Research [6][7] indicated that advancements in Vehicle-to-Vehicle (V2V) communication and the sharing of trajectory prediction data among autonomous vehicles improved traffic flow and reduced accident rates in urban environments. Our study originates from the basic principles of vehicle-to-vehicle communication and situational awareness. Improving the situational awareness of autonomous vehicles is achievable with the integration of artificial intelligence (AI), particularly deep learning. The need of situational intelligence, capable of comprehending and reacting to intricate and dynamic circumstances, was unequivocally demonstrated for urban driving [6].

Deep learning methods significantly enhance situational awareness in autonomous systems by discerning intricate patterns from data.

Research studies [8], [9] used deep learning models, including LSTM, to forecast future states of autonomous vehicles as behavior prediction functions, therefore enhancing awareness of possible risks to mitigate. Furthermore, [10] used an LSTM-based AI model using spatial coordinates to forecast the future trajectories of Target Vehicles (TV), however it necessitates extensive simulation data for training the LSTM model. There is a need for customized strategies that use AI methods to tackle the distinct issues of off-road navigation. Management of autonomous vehicles in difficult off-road environments need sophisticated systems that can adjust to changing topography and dynamic impediments. route-tracking controllers, such as Pure Pursuit, modify the steering angle in accordance with route curvature. [11] The Stanley control path-tracking method identifies lateral and direction mistakes and has shown efficiency in off-

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road scenarios; nevertheless, it lacks resilience in the presence of adjacent vehicles. In this setting, the Model Predictive Controller (MPC) [14], a restricted dynamical optimum control issue, tackles the resilience, stability, and smoothness of the control strategy. The methodologies detailed in [15] and [16], including Model Predictive Control (MPC) supplemented by deep learning predictions, were used to improve collision avoidance in urban settings; however, they are constrained in difficult off-road conditions.

Although Model Predictive Control (MPC) provides resilience and stability, its efficacy in managing multi-vehicle interactions, particularly in demanding off-road situations, is constrained. Furthermore, the integration of Model Predictive Control (MPC) with artificial intelligence methodologies in off-road settings is inadequately investigated, highlighting a substantial need in contemporary research efforts.

This work presents a revolutionary architecture designed to improve the control of autonomous vehicles in off-road conditions via the use of AI-

predicted trajectories. Off-road navigation has distinct obstacles because to always changing circumstances. Our methodology, the Potential-Rate Long Short-Term Memory (PR-LSTM) network, is engineered to accurately forecast vehicle trajectories in such contexts.

We evaluate the effectiveness of our strategy by integration with Model Predictive Control (MPC)-enabled autonomous vehicles. Furthermore, our study presupposes the implementation of Vehicle-to-Vehicle (V2V) communication to enable the transmission of prospective trajectory data between Autonomous Vehicles (AVs) and Traditional Vehicles (TVs).

This paper will be structured as follows. We will examine the off-road simulation platform, the PR-LSTM-based trajectory prediction system, and the vehicle control framework. Section 3 examines the outcomes of the AI-prediction PR-LSTM model as applied to three distinct autonomous vehicle management strategies: the gradient-based steering (GBS) method, conventional model predictive control (MPC), and MPC with AI-predicted trajectories. Ultimately, the conclusions will be presented in the Section

Methodology

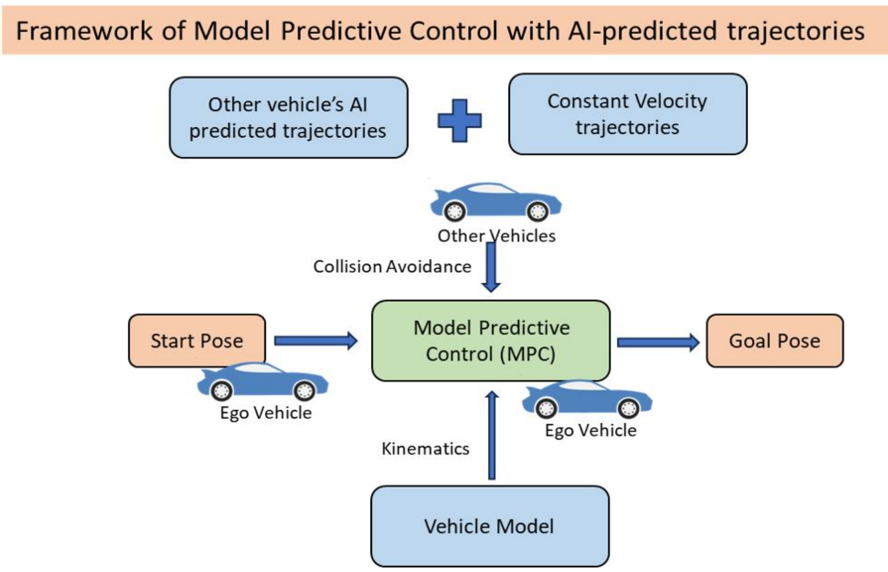

Figure 1: MPC with AI-based Prediction

AI-generated trajectory-based vehicle control in off-road environments presents significant challenges yet holds substantial implications for autonomous vehicle navigation. This research examines the evaluation of an AI-generated trajectory prediction intended for an off-road setting. The capability of autonomous vehicles to successfully traverse off-road settings relies on the integration of sophisticated algorithms that provide accurate trajectory data and implement effective control strategies.

Section 2.1 delineates the creation of an off-road platform used for the generation of AI-predicted trajectories and the implementation of control algorithms. The structural components of the environment are meticulously analyzed, highlighting the features that emulate the intricacy of off-road landscapes. Section 2.2 provides a detailed exposition of the fundamental approach for AI-driven trajectory prediction and its incorporation with Zero-Order Hold (ZOH) trajectory [17].

Section 2.3 subsequently examines the assessment of diverse control systems used in this investigation, encompassing Gradient-Based Steering (GBS), Model Predictive Control (MPC), and MPC coupled with an AI-model framework. These control methodologies are examined, focusing specifically on their robustness and adaptability to off-road conditions. Section 3 ultimately presents the results derived from the comparison of the previously mentioned control algorithms.

Figure 2: Birds Eye View of simulation environment

Proactive Model Predictive Control with AI-Predicted Trajectory (MPC-AI) Employing the Model Predictive Control (MPC) paradigm, control inputs are optimized over a predictive time horizon, allowing the vehicle to make intelligent choices based on current and projected future circumstances. This optimization approach considers the system model, constraints, environmental factors, and safety standards to provide optimum trajectories and control inputs for autonomous vehicles (AVs). This work enhances traditional MPC by AI-based PR-LSTM predictions of surrounding vehicle trajectories. The MPC is designed using a non-linear two-dimensional kinematic system model, as delineated in equation 9, which fails to include rollover concerns during acute turns. The cost function specified in equation 8 imposes penalties for departures from the objective and for possible accidents with adjacent cars. The collision cost includes forecasts from adjacent cars, concentrating only on those inside the forward trajectory of the ego vehicle at each time step k. Poses of adjacent cars, sNV,k = [xNV,k; yNV,k], and their velocities derived from PR-LSTM projections.

Experimental Setup

Training datasets including temporal positional data were collected from a fleet of 60 cars outfitted with LiDAR sensors functioning in an off-road simulation environment inside Unreal Engine [10]. The computing machinery used for this assignment has a formidable setup, including a Threadripper Pro 3995WX CPU with 64 cores, in conjunction with RTX A6000 GPUs.

MATLAB 2023a functioned as the main software platform for executing simulations and training time series forecasting, specifically using the LSTM Deep Learning model.

The training dataset for the PR-LSTM model consisted of data from 460 cars, whilst a separate testing dataset including information from 60 vehicles was used to assess trajectory predictions.

Table 1 presents a summary of the hyperparameters and architecture of the PR-LSTM model, while Figure 5 illustrates the model's training loss. The PR-LSTM model's test outcomes indicated a mean root mean squared error (RMSE) of 0.07 for the prediction of the upcoming time step, evaluated using data from five cars. Moreover, Figure 6 depicts the efficacy of the PR-LSTM model in monitoring the potential of an individual vehicle. The network utilizes four channels to represent attractive and repulsive potential rates, successfully predicting trajectory information for the subsequent step.

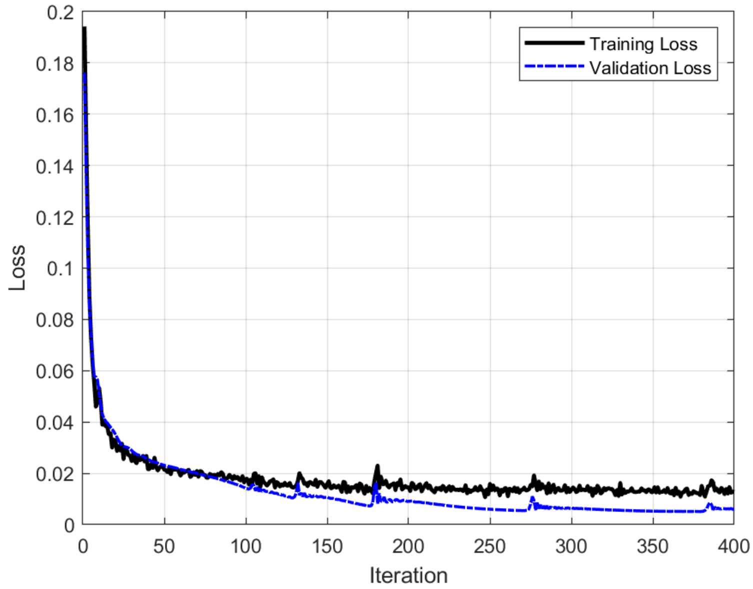

Figure 3: PR-LSTM Training Loss

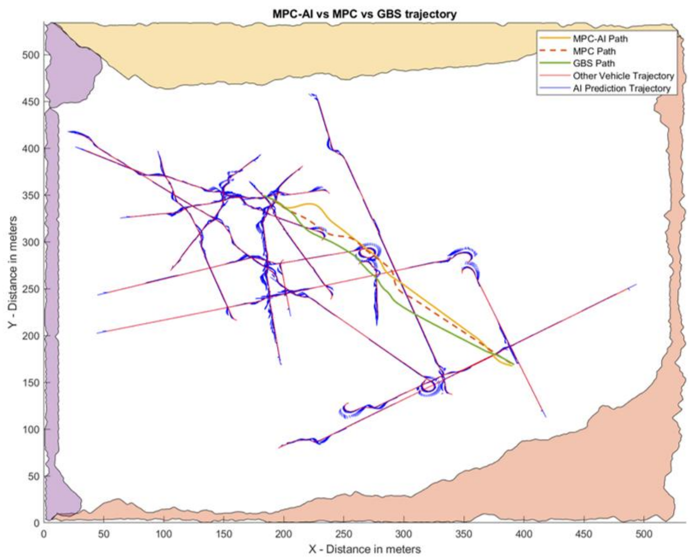

Figure 4: GBS, MPC, MPC-AI trajectories with AI-predicted trajectories

shown by the tight correspondence of the anticipated trajectory (seen by the red dashed line) with the original trajectory potential rate. AI trajectories in relation to the AI-predicted future trajectories derived from data collected from 15 vehicles. AI trajectories consistently surpass ZOH trajectories across essential metrics. The AI trajectories have a variation of 0.35, which is lower than the variance of 0.51 seen in the ZOH trajectories. Furthermore, the highest error linked to AI trajectories is significantly reduced at 16.97, in contrast to the maximum error of 17.30 for ZOH trajectories. The average error for AI trajectories is 4.41, far surpassing the ZOH trajectories, which have an average error of 5.86. These findings emphasize AI's exceptional accuracy and efficacy in trajectory planning, highlighting its potential to improve performance in autonomous vehicle planning and control systems.

Results and Analysis

The PR-LSTM model visualizes the AI-predicted trajectories for 15 adjacent cars used in the control simulations, as seen in figure 5. The prediction trajectories, used only for the MPC-AI model, are shown in blue at each time step for a horizon length of N=10. The original route trajectories of underlying barriers are shown in red, while shaded polygons of diverse hues delineate off-road borders. GBS, MPC, and MPC-AI separately govern the trajectories of the ego vehicle, with 15 nearby cars shown in green, dotted red, and dark yellow, respectively. Each ego vehicle, regulated by its designated control scheme, utilizes algorithms specified in sections 2.3.1 and 2.3.2 for GBS, MPC, and MPC-AI. The restrictions for angular velocity and linear velocity remain aligned with those described in section 2.3.2. Figures 5 and 6 depict the distance to collision for vehicles 3 and 15, respectively, over the designated time period.

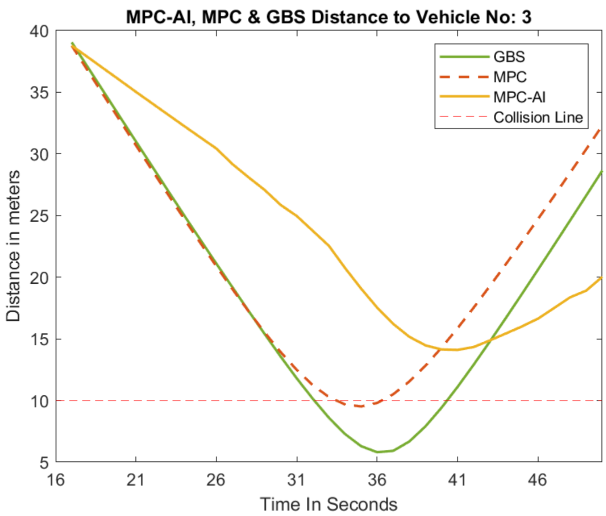

Figure 5: Sample result 1: Collision response of control algorithms

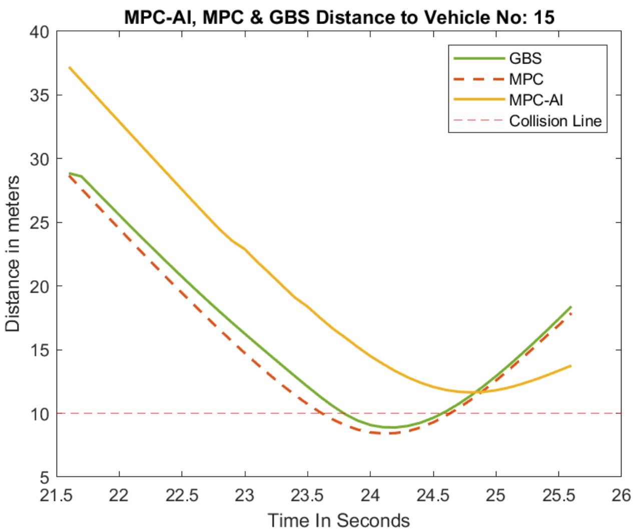

Figure 6: Sample result 2: Collision response of control algorithms

Both GBS and MPC paths encounter encounters with impediments, with MPC demonstrating marginally superior performance relative to GBS while pursuing the same aim. In contrast, the MPC integrated with the AI model effectively prevents collisions with obstructions by a considerable margin. `

The simulation results of the comparative study of AV control systems are , focusing on essential metrics pertaining to collision avoidance and proximity management. GBS has a negative closest distance of -4.2 meters, indicating potential collisions with objects. This is substantiated by the documented occurrence of two crashes. Likewise, MPC has an enhanced minimum distance of -1.6 meters, accompanied by two collision occurrences.

Conclusion

This research presents an innovative method for autonomous vehicles (AVs) to traverse off-road terrains by using AI-predicted paths while adeptly circumventing obstacles. The proposed methodology markedly improves vehicle autonomy, facilitating agile and responsive navigation during interactions with other vehicles. The results of this research highlight the effectiveness and advantages of the suggested method.

Integrating predictive control methods, the amalgamation of classical Model Predictive Control (MPC) with artificial intelligence allows effective obstacle avoidance grounded in established models and restrictions. Although traditional Model Predictive Control (MPC) offers a solid basis for regulation, the incorporation of artificial intelligence into MPC has the potential for more adaptable and dynamic responses, hence improving performance, especially in difficult off-road environments.

Future research will involve validating the developed algorithm through a high-fidelity simulation model and real-world experiments using an actual off-road autonomous vehicle. The high-fidelity simulation model will be tested for rollover, which is essential for real-world safety, particularly for vehicles operating at elevated speeds, to guarantee enhanced generalizability. The shift from simulation to real-world testing is a vital step in confirming the effectiveness and practical relevance of the suggested method in actual circumstances.

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