Enhancing Autonomous Vehicle Control: Adaptive Neural Network-Based Control in AirSim Simulator

Presented by ~

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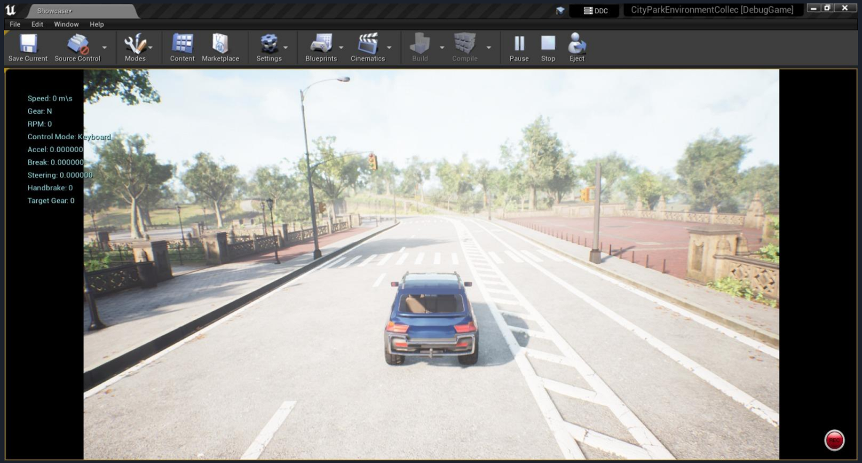
Problem statement

In the realm of autonomous vehicles, the efficient integration of realistic data, advanced control strategies, and accurate deep learning models poses a significant challenge.

The project aims to address the complexities involved in creating a seamless autonomous driving system by utilizing Microsoft Airsim for data collection, implementing a Model Predictive Controller (MPC) for optimal control, and employing imitation learning to fine-tune a deep learning model for predicting critical driving parameters.

The challenge lies in achieving a robust and reliable system that can adapt to diverse real-world scenarios, ensuring safety and performance. The model needs to be able to adapt to various situations like sharp and wide turns and gradual smooth turns without colliding with the obstacles around. It is also important to not have a jittery/ wavy output.



Related works and our approach

- Related Works :Researchers have implemented imitation learning on autonomous cars in a sim setup by collecting data using basic controllers such as PD, PID and gamepad on carla simulator.
- Our implementation uses Airsim simulator which is a more user intuitive software with various city environments. We also used the MPC controller to collect data for a smoother trajectory and less Jittery and wavy behavior. This approach helped us collected a data with varied distribution, that helps in creating a model which is suited for most environments.
- Our approach unlike other existing methods we stated gives a model which trains with various hyperparameters. The model gives steering angle as the output while taking in image data and the current state of the car of as the input.

Data collection using Model Predictive and Proportional–Integral–Derivative controllers:

For both the controllers, waypoints (x and y coordinates) are generated that represent the path that needs to be taken by the car. These waypoints are essential for generating a reference trajectory that the vehicle should follow. These controllers then optimize the vehicle's control inputs (throttle and steering) over a finite time horizon while taking into account the desired trajectory represented by these waypoints.

While the sim is running, the Airsim provides functionality to record the scenario and provide images for the data to be used by our Neural Network.

Training:Validation:Test split is = 7:2:1 in our case and HDF5 files are saved to pass through the training part.

Model Predictive Controller - Cost function:

$$cost = \sum_{i=1}^{N} \{c_1 \cdot \mathrm{CTE}_i^2 + c_2 \cdot (\mathrm{v}_i - \mathrm{v}_0)^2 + c_3 \cdot \delta_i^2 + c_4 \cdot a_i^2 + \ldots\}$$

where δ and a are the steer angle and throttle (actually, acceleration), the $\{c_i\}$ are coefficients chosen by the user, and v_0 is the target speed with which we want the car to drive.

PID Controller - Control Function:

$$u(t) = K_\mathrm{p} e(t) + K_\mathrm{i} \int_0^t e(\tau)\,\mathrm{d}\tau + K_\mathrm{d} \frac{\mathrm{d}e(t)}{\mathrm{d}t}$$

where u(t) is PID control variable, K_p is proportional gain, e(t) is error value, K_i is integral gain, d*e* is change in error value, d*t* is change in time

Annotations

airsim_rec - Notepad

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VehicleName	TimeStamp	POS_X	POS_Y	POS_Z	Q_W	Q_X	Q_Y	Q_Z	Throttle	Steering	Brake	Gear	Handbrake	RPM	Speed	ImageFile
PhysXCar	1702451192295	12.9902	1.02795	4.53922	0.993812	-0.000484918	0.00101799	0.111072	0.50034	0.185759	0	1	0	2147.07	5.02503	img_PhysXCar__0_1702451192293633700.png
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PhysXCar	1702451192703	14.4269	1.44432	4.53271	0.990665	-0.00110131	0.00193582	0.136301	0.653615	0.014024	0	1	0	2098.61	5.01737	img_PhysXCar__0_1702451192701666200.png
PhysXCar	1702451192826	14.9086	1.58461	4.53158	0.990412	-0.000732415	0.00259501	0.138117	0.653615	0.014024	0	1	0	2225.23	4.8189	img_PhysXCar__0_1702451192824170900.png
PhysXCar	1702451192961	15.3691	1.71782	4.53484	0.990349	-0.000838463	0.00245428	0.13857	0.653615	0.014024	0	1	0	2326.73	5.02168	img_PhysXCar__0_1702451192960295900.png
PhysXCar	1702451193046	15.6918	1.81129	4.52783	0.990269	-0.00115945	0.00311312	0.13913	0.447604	0.120906	0	1	0	2317.69	4.86503	img_PhysXCar__0_1702451193045062100.png
PhysXCar	1702451193166	16.1721	1.96582	4.52372	0.989388	-0.00251775	0.00370215	0.145231	0.447604	0.120906	0	1	0	2229.43	4.91344	img_PhysXCar__0_1702451193165156700.png
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PhysXCar	1702451193426	17.1075	2.28745	4.5178	0.987354	-0.00423107	0.00383789	0.158428	0.520277	0.12688	0	1	0	2179.25	4.93316	img_PhysXCar__0_1702451193424154600.png
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PhysXCar	1702451194244	20.0034	3.48348	4.5013	0.979565	-0.00840406	0.0016709	0.200944	0.542374	0.138957	0	1	0	2097.32	5.01508	img_PhysXCar__0_1702451194242018100.png
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Model creation

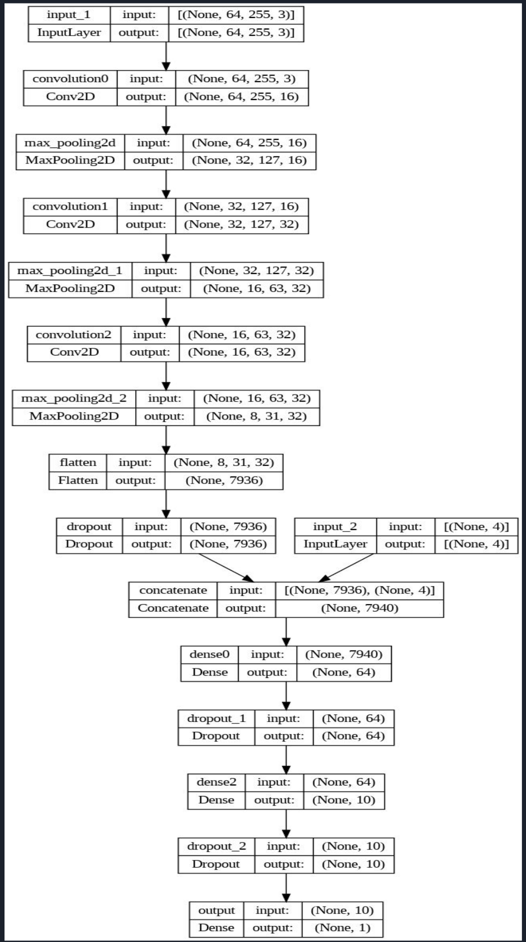
Input 1 : Image input

Input 2 : State input (Speed, brake, steering, throttle)

Output : Steering angle

Throttle is maintained in such a way that the speed does not exceed a decided speed limit.

The model is a hybrid neural network combining convolutional layers for image processing and dense layers for integrating image and auxiliary state data, structured for tasks requiring the fusion of visual and contextual information. It uses convolutional layers for feature extraction from images, followed by dense layers to process these features along with additional state inputs, and is optimized with Nadam and mean squared error loss.



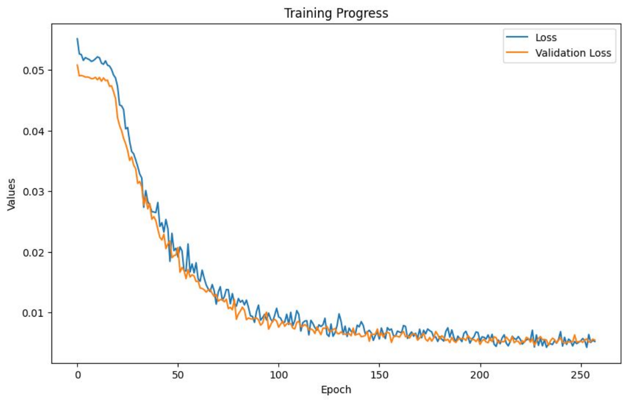
Results

Loss : Mean squared error.

The data was collected using MPC and PID controller and trained on each one of them to produce results.

There are two videos which consist of two scenarios one in which the car has to take gradual turns over the course and one which it has to take a sharp turn. The result outputs are present in the link.

The data collected with images and their labels are present in this link.



Training and validation loss on MPC dataset

Sharp turn using the trained model

Gradual turn using the trained model

Technical Challenges

1. Using the entire image for the training is not an option as the background can cause issue with the predictions due to the feature extraction nature of the model. So to select the right ROI for the image was concern.
2. To tune the hyperparameters like zero drop percentage (percentage of zero value data to exclude) was a challenge.
3. To figure out the best model is often a challenge as sometimes the model with lowest error does not yield the best practical output. So it is important to avoid overfitting and select the model with low error but decent outputs.
4. Making the model with the right architecture that suits our application also was a huge challenge, we did use a lot of reference from various sources to get to where we got.

Limitations

Simulation-to-Reality Gap:

Works: The model performs well in scenarios that closely resemble the conditions encountered during training in the simulation.

Doesn't Work: Performance may degrade when exposed to real-world conditions that deviate significantly from the simulated environment.

Environmental Variability:

Works: The model adapts effectively to a diverse range of environmental conditions encountered during training.

Doesn't Work: Extreme or uncommon scenarios not adequately represented in the training data may challenge the model's generalization.

Limitations

Real-time Challenges:

Works: The model responds effectively to dynamic scenarios within the constraints of its training setup.

Doesn't Work: Real-time adaptability may be constrained by the model's training environment, impacting responses to rapid changes in road conditions.

Sensor Dependency:

Works: The model effectively utilizes vision-based perception for decision-making.

Doesn't Work: Limitations may arise when the system encounters scenarios where additional sensor modalities, beyond vision, are crucial for comprehensive understanding.

Future work

Real-time Adaptation and Learning:

Approach: Implement a continual learning framework for real-time model updates, using online learning and incremental training techniques. Explore dynamic parameter adjustments for adaptability to changing environmental conditions.

Sensor Fusion Integration:

Approach: Integrate multiple sensor modalities, such as LiDAR and radar, using sensor fusion algorithms like Kalman filtering or deep sensor fusion networks. Develop a comprehensive perception system leveraging each sensor's strengths.

Adversarial Training for Robustness:

Approach: Augment the training dataset with adversarial examples or simulated attacks, training the model with robust optimization techniques and regularization methods. Utilize adversarial training datasets mimicking realistic challenges. Regularly update the model's defenses for resilience against emerging threats.