EECS 753 Project Proposal

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Problem Statement

As the sector of autonomous vehicles mature, neural network (NN) are becoming more prevalent in autonomous vehicles as a means to simplify and accelerate traditional algorithms used for vehicle guidance, navigation, and control (GNC). However, unlike the traditional algorithms, NN have no output smoothness guarantee so small perturbations in the network input can lead to drastically different outputs which can often lead to high jerk control inputs.

Motivation

As neural networks are universal approximators with the proofs of such generally using the network architecture and properties of the activation functions [1], they are often candidates to replace other algorithms when speed is critical. Various works show the prevalence of NN within various autonomous cars [2, 3, 4] although NN are often not used to replace the entire logical chain from environmental perception to control as in [2]. However, when NNs replace the entire logical train, the vehicle can be unsafe and crash whereas the NN that only replace guidance and/or navigation in the vehicle GNC yield safer behavior. Previous work has used NNs to output Bézier curves for smooth navigation curves with an underlying pursuit curve controller for autonomous racing [5] but this relies on the vehicle having spatial information either through simultaneous localization and mapping or global positioning systems. Small indoor autonomous vehicles may not have the computational resources or sensors for real-time GNC but the vehicles may be able to utilize the combination of CNN and Bézier curves to schedule smooth control commands from vision and outperform platforms using CNN purely to generate commands from vision.

Proposed Solution

The DeepPicar is a remote control model car that has been built to drive around a marked track using a convolutional neural network (CNN) hosted on a Raspberry Pi [2]. While it originally used a CNN to generate steering angle control commands, this project would use a CNN on DeepPicar as a control scheduler using Bézier curves to generate smooth steering angle commands. This change in the utilization would allow for smooth control outputs and potentially computational resource saved as the Bézier CNN may be able to run at a lower rate than the original CNN while still allowing for real-time GNC.

Project Outline

This project can be broken down into three parts over the month of April starting April 5, 2021:

Part 1) Train CNN based data original to the DeepPicar [2] or a similiar data set. Weeks 1-3.

Part 2) Implement the real-time controller for DeepPi car where a real-time task convolutional neural network (CNN) schedules the command steering angle for some time window and an inner loop real-time controller implements the steering angle schedule. Week 2-3.

Part 3) Run experiment to determine performance. Of particular note is the accuracy of the DeepPicar following a racetrack as well as the computational resource cost of this overall control scheme compare to the CNN used in Ref [2]. Week 3-4.

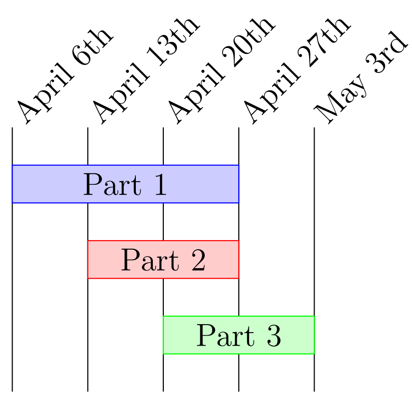

Figure 4.1: Timeline Gantt Chart

Final outcomes of this project is a trained convolutional neural network outputting a Bézier curve for control scheduling and some performance benchmarking to determine the change in resource utilization form the original CNN in [2]. Benchmarking of the proposed solution should be performed on the DeepPicar and have quantitative CPU resource effects such as scheduled CPU time and worst-case execution time in addition to qualitative driving performance effects such as how far around the track DeepPicar drives and how many times the car drives outside the track bounds.

References

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