AutoDrive
Design Specification

Team Pink Flamingo

Jianjie Liu (CS)
Michael Morscher (ENP)
Phoebe Yang (CS)

Sponsors

JK Pollard
Jivko Sinapov

November 16, 2018
Version 1.0

Table of Contents

Introduction

The mission of AutoDrive is to **build and train a miniature self-driving car to investigate real-world problems in safety, behavior, and computation**.

This project was designed with three initial parallel efforts — building the hardware of the physical car, training the self-driving model using a simulator, and conducting human factors research to inform the ideal autonomous driving behavior. These efforts will then be integrated to form our proof-of-concept self-driving car, enabling us to conduct further research with real-world implications and experiment with variations on the self-driving model.

This design specification provides an overview of our project approach and implementation choices for the three parallel efforts underway. It is intended to be updated with any project developments, and contains sufficient depth of information to inform a software and hardware testing plan.

Each team member brings their technical expertise to contribute to this project — Jianjie in self-driving models and hardware engineering, Michael in transportation safety research and systems engineering, and Phoebe in software architecture and machine learning. We can be reached at the following email addresses with any questions, concerns, or comments:

Jianjie.Liu@tufts.edu

Michael.Morscher@tufts.edu

Yu.Yang@tufts.edu

Limitations

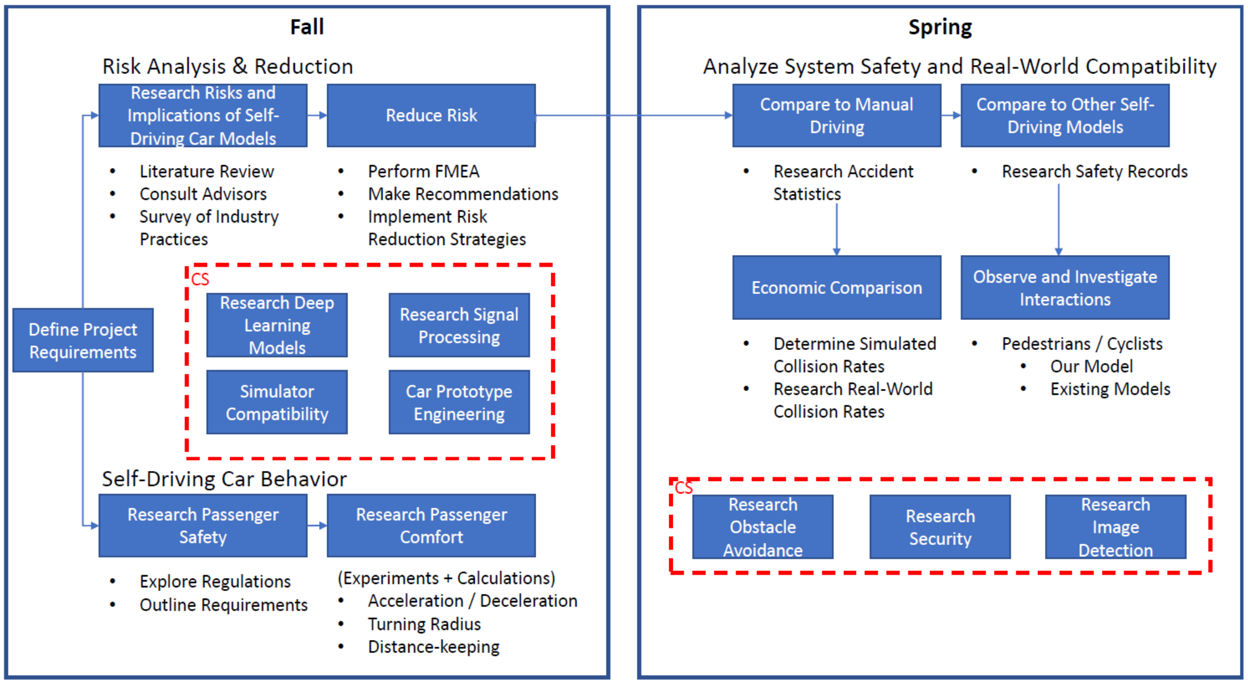
This document is intended as an overview of the current state of the AutoDrive project. For this reason, it does not include in-depth research results, data, or implementation details. It also does not include the details of work which will be completed in the Spring semester other than an overview of the planned approach.

This is also not an full technical report on each project milestone. We will refer to our GitHub repository for the complete source code produced and for more details on technical challenges and solutions.

Research Approach

System Safety & Behavior

The following diagram summarizes the scope of our research into system safety and behavior:

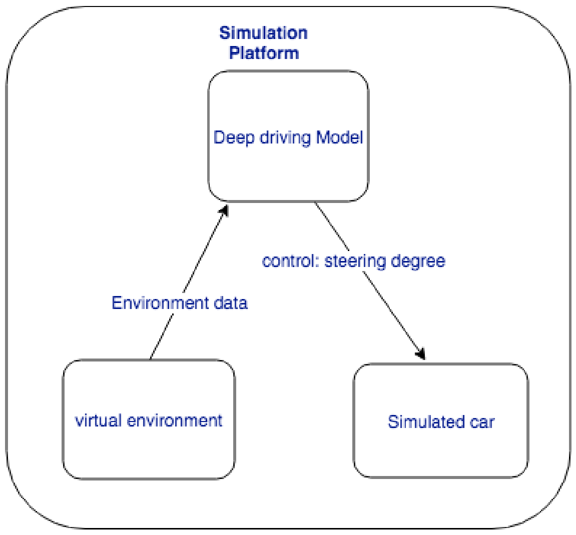

Fall
Risk Analysis & Reduction
Research Risks and Implications of Self-Driving Car Models
Reduce Risk
• Literature Review
• Consult Advisors
• Survey of Industry Practices
• Perform FMEA
• Make Recommendations
• Implement Risk Reduction Strategies
Define Project Requirements
CS
Research Deep Learning Models
Research Signal Processing
Simulator Compatibility
Car Prototype Engineering
Self-Driving Car Behavior
Research Passenger Safety
Research Passenger Comfort
• Explore Regulations
• Outline Requirements
(Experiments + Calculations)
• Acceleration / Deceleration
• Turning Radius
• Distance-keeping
Spring
Analyze System Safety and Real-World Compatibility
Compare to Manual Driving
Compare to Other Self-Driving Models
• Research Accident Statistics
• Research Safety Records
Economic Comparison
Observe and Investigate Interactions
• Determine Simulated Collision Rates
• Research Real-World Collision Rates
• Pedestrians / Cyclists
• Our Model
• Existing Models
CS
Research Obstacle Avoidance
Research Security
Research Image Detection

For each research component or group of components above, the following approach will be taken:

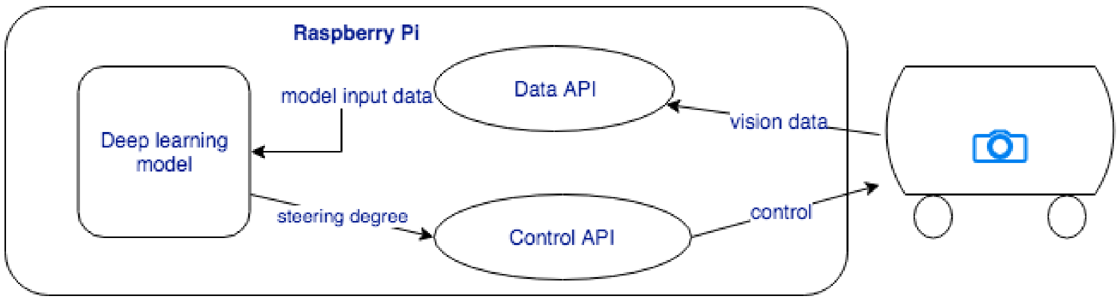
1. Conduct a literature review of human factors and transportation industry sources
2. Determine gaps in previous research
3. Consult sponsors / advisors on filling in these gaps
4. Fill in the gaps by running an independent investigation, interviewing industry experts, and/or pulling in relevant findings from other fields
5. Organize results as a deliverable, in the form of a formal write-up or proof-of-concept demonstration

Self-Driving Model Frameworks

Research and implementation of the self-driving model will be organized under two frameworks. The first framework involves **training and testing** the self-driving model:



The second framework involves **deploying** the self-driving model:

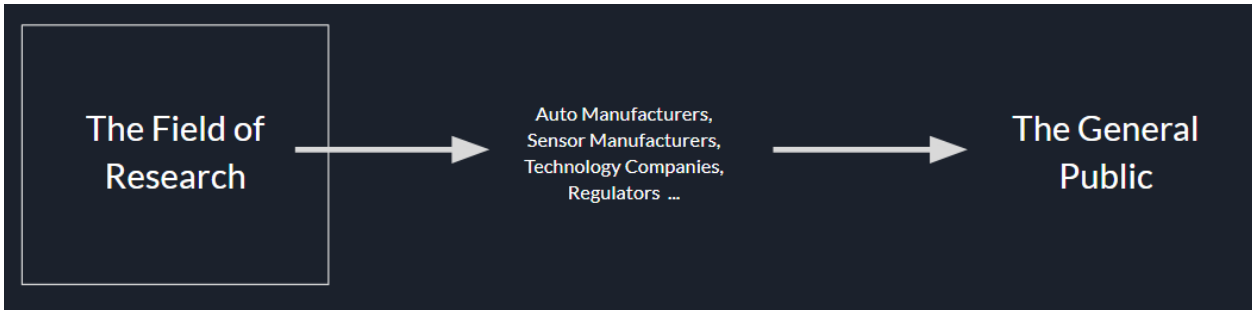


The research approach in building the self-driving model follows the order of the required system functions as indicated by the arrows in the diagrams above.

Stakeholders, Needs & Requirements

AutoDrive is an interesting project in that the end result is *not* a software application or physical product. **The “products” of this project are research findings which will introduce valuable new knowledge to the public domain.** This will be accomplished through building a sensor-connected miniature vehicle supported by a self-driving model, which is a significant deliverable but not a product in and of itself. It will be foremost a proof-of-concept of building an extensible self-driving model, and later on, a tool for both implementing research conclusions and discovering new insights.

The following diagram depicts the direct and indirect stakeholders of the AutoDrive project:


The Field of Research
Auto Manufacturers, Sensor Manufacturers, Technology Companies, Regulators ...
The General Public

Our direct stakeholder is essentially “the field of research”, with significant implications in extensibility to the real world.

The needs and requirements of our stakeholders can be summarized as follows:

Our stakeholders need:

- Research findings on best practices for autonomous models from an objective, academic perspective.
- Open sharing of best practices knowledge in system design, behavior, and safety, unlike closed knowledge of private autonomous vehicle manufacturers.

Our research investigations and findings shall:

- Extend trusted previous research with new approaches.
- Address ethical and safety implications of the findings.
- Be openly accessible to inform objective safety and behavior standards.

Materials & Technologies

This project utilizes both hardware and software as follows:

Physical Materials

1. Radio Wave Controlled Car (Tamiya TT02)
2. Raspberry Pi 3b
3. Raspberry Pi Camera
4. HC-SR05 Ultrasonic Sensor
5. Power Bank
6. Breadboard
7. Wires

Software Dependencies

1. Python3.6
2. Matplotlib 2.2.2
3. Numpy 1.12.1
4. Keras 1.2
5. Tensorflow 1.1
6. Sklearn 0.20.0
7. pigpio (Natively installed on Raspberry Pi OS)
8. picamera (Natively installed on Raspberry Pi OS)
9. Udacity Self-Driving Car Simulator (https://github.com/udacity/self-driving-car-sim)

Software Modules Developed

The source code of all the modules mentioned here can be found on GitHub.

Data API

This interface is responsible for processing raw images from the physical camera and converting them to ‘PIL.image’ (Python Imaging Library) objects for further processing. 'PIL.image' can be easily converted to other library objects such as a 2D ‘numpy.array’. Much of this module relies on the library ‘picamera’, an SDK natively installed on the Raspberry Pi operating system.

Control API

We designed two separate objects to separately control the longitudinal (forward) motion and transverse (steering) motion of the car:

Servo.py

Defines the “Servo” object that controls the physical servo in the car with pulse width modulation (PWM). This module can turn the servo in a steering angle from a continuous range of [-18.5°, 18.5°]. This is established by utilizing a linear relationship between steering angle and the pulse width needed to induced the angle on the servo. This linear relationship was found experimentally (see GitHub for more details) and is defined as follows:

$$y = 17.9*x + 1439$$

Where 'y' is the pulse width needed to induce the desired steering angle, 'x', in degrees.

We define the axis of orientation with respect to the car, so left turns have negative steering angles and right turns have positive steering angles. We use the library method (link to documentation) 'pigpio.pi.set_servo_pulsewidth()' to physically simulate the signal with the desired pulse width to control the servo. However, the library method does not specify the units of the pulse width, but we suspect it to be in milliseconds.

Methods:

- 'turn()': turn the servo within the range [-18.5°, 18.5°].
- 'left()' : turn the servo into the minimum steering angle (-18.5°).
- 'right()' : turn the servo into the maximum steering angle (18.5°).
- 'neutral()': set the servo to neutral position (0° steering angle).

Motor.py

Defines the “Motor” object that controls the physical motor in the car with pulse width modulation (PWM). At the current stage, this module provides only a trivial method to move the vehicle forward at a constant minimum velocity. Again, we use the library method (link to documentation) 'pigpio.pi.set_servo_pulsewidth()' to physically simulate the signal with the desired pulse width to control the motor.

Methods:

- 'calibrate()' : calibrate the motor to the appropriate range of signal.
- 'moveForward()' : move the motor in positive direction at a constant velocity.
- 'stop()': stop the motor.

Deep Learning Model

The complete source code of this module can be found on GitHub.

We instantiated and trained an end-to-end convolution neural network (CNN) model using Keras. The model takes in a 64x200 image and outputs steering commands in units of radians to keep the vehicle in the middle of a track. We use the CNN architecture published on Nvidia’s End to End Learning for Self-Driving Cars paper with small modifications:

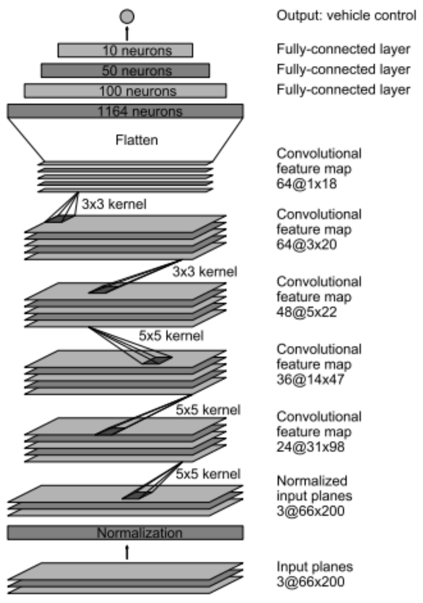


Figure 4: CNN architecture. The network has about 27 million connections and 250 thousand parameters.

The model is a convolution neural network that accepts a 64x200 (The original model takes in 66x200) pixel-wide image with 3 channels and outputs one node, which is the steering command. This CNN consisted of a normalization layer and 5 convolution layers followed by 4 fully connected layers.

For more details on training this neural network, please refer to this GitHub repository.

The performance of this model on two simulated tracks is recorded in separate videoes: Track1 and Track2.

Functionality

Current Functionality

1. The prototype will autonomously steer itself around a track at constant speed without crossing the lane lines

Planned Features

1. Recognize traffic signs, traffic lights, speed bumps and other traffic control agents
2. React to traffic lights: stop the car when the camera detects a red traffic light, move forward as the light turns green, and etc.
3. Detect hindering obstacles and plan path to circumvent the obstacle if possible
4. Implement a representation of recommended acceleration bounds from human factors research
5. Explore the potential benefits of using a combination of motion model and model predictive control instead of an end-to-end neural network in generating actuations for the vehicle.

Proof-of-Concept Product Design

Car Prototype

Hardware Components:

1. Radio Wave Controlled Car (Tamiya TT02)
2. Raspberry Pi 3b
3. Raspberry Pi Camera
4. HC-SR05 Ultrasonic Sensor
5. Power Bank
6. Breadboard
7. Wires

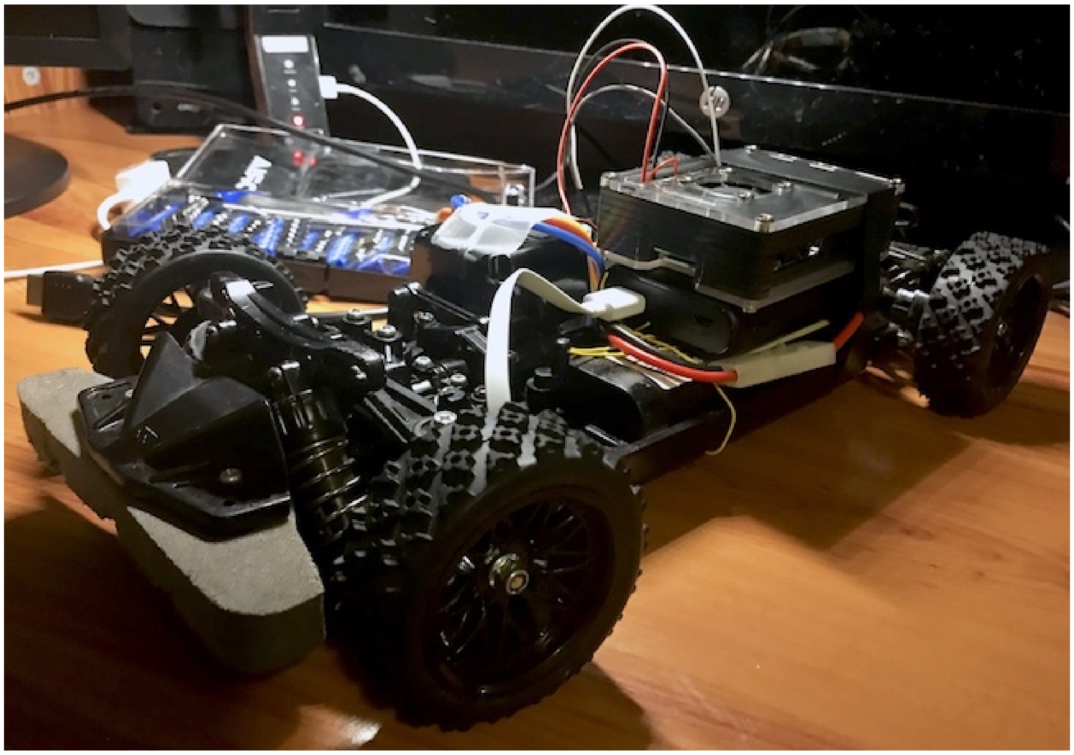
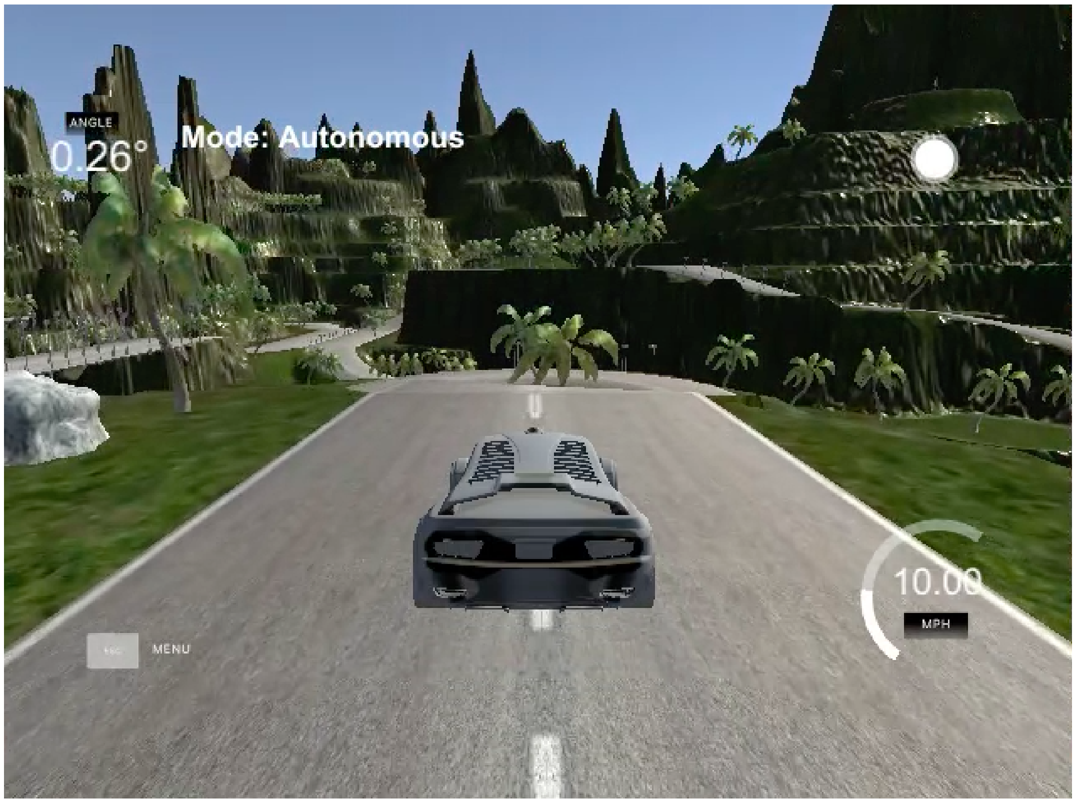


Photo of car prototype

Simulation

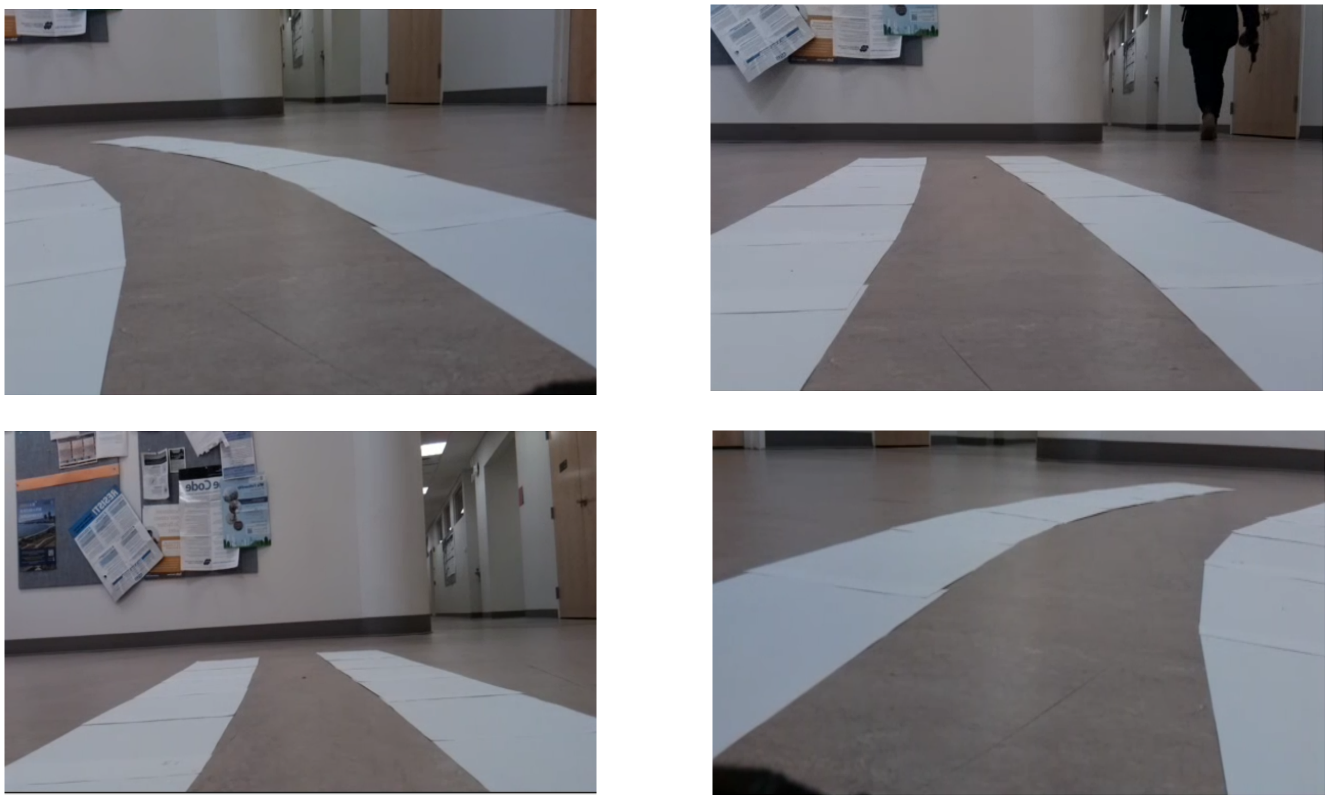
We trained and tested our model using a Unity simulator which simulates the track environment and supports both the training mode and the autonomous mode. We collect data from the training mode to train a model, then we test the model in the autonomous model to see how it performs. A couple of measures of success include: (1) the car reacted to the change in tracks and steers itself at turns, (2) how long the car can drive itself in the autonomous mode without running off-track, and (3) how stable the car is in terms of velocity, steering speed, and acceleration.



Screen capture of self-driving model running in the simulator

Proof-of-Concept Integration

After training and testing the model in the simulated environment, we want to see how the model performs using real-world data. We collected snapshots of “paper tracks” with the camera on the car and fed the data to the model. Theoretically, the model should output a steering angle close to the proximate angle of the track. We tested the model in 3 basic scenarios: (1) left curve, (2) straight track, and (3) right curve.



Training images for real-world driving track

Here are results corresponding to the sample training images above which exhibit the functionality of our model:

Sample Image	Steering Angle	Throttle
left_1	-0.07146952301263809	0.079644
right_1	0.03908034786581993	0.8582879999999999
straight_1	-0.03622625395655632	1.0337062
straight_2	-0.021753234788775444	0.4809422

We observe that the model can output a correct steering direction based on the track condition. When the track is extending towards the left, the model outputs a left/negative steering angle -0.07; and when the track is turning right, the model outputs a right/positive steering angle 0.03. Based on the results from the test, we are confident that the model performs reasonably on real-world image data.

We plan to integrate the software model with the hardware prototype by deploying the model on the Raspberry Pi. All relevant data transformations will be supported by the Data API and the Control API *(see “Software Modules Developed”)*.

References

AutoDrive Project Repo:
https://github.com/JohnGee96/AutoDrive

Deep Learning Model Project Repo:
https://github.com/JohnGee96/CarND-Behavioral-Cloning

Simulation Track 1:
https://www.youtube.com/watch?v=SJyCEcUxbe0

Simulation Track 2:
https://www.youtube.com/watch?v=Utz5BzwYJ1Y&t=65s

Udacity Autonomous Vehicle Simulator:
https://github.com/udacity/self-driving-car-sim

Nvidia's End-to-End Learning for Self-Driving Cars:
http://images.nvidia.com/content/tegra/automotive/images/2016/solutions/pdf/end-to-end-dl-using-px.pdf

PIGPIO Library Documentation:
http://abyz.me.uk/rpi/pigpio/python.html#set_servo_pulsewidth