Self driving toy car

Project for 3D Computer Vision lecture, summer term 2020

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***Abstract*—This report describes the self driving car toy project done in the 3D Computer Vision lecture at Heidelberg University. The goal is to train neural networks so that the given car can drive autonomously on a track.**

***Index Terms*—autonomous driving, computer vision, image processing, neural networks**

I. Getting started

For getting started an operating system needs to be flashed onto the Raspberry Pi 3 B+ which is mounted into the car. Through the Raspberry Pi Imager the Pi OS 32-bit in release 2020-05-27 was flashed onto the SD card. The OS is a port of Debian with the Raspberry Pi Desktop and comes with an integrated configurator to enable SSH, VNC, the camera, SPI and I2C. During our project several different approaches are used. Roughly divided into an approach with and without machine learning. The first approach is classical image processing without machine learning by using OpenCV.

II. Image Processing without ML

The goal of this approach is to let the car drive autonomously on the track without using machine learning. Therefore the approach can be roughly divided into two subtasks, the image processing with OpenCV and the driving. OpenCV is an open library for computer vision and machine learning of which the first part is used.

A. Driving

Once again the driving task can be divided into the following two subtasks, steering and throttle. The Raspberry is mounted on the vehicle together with a servo and an Arduino PCA9685 controller. The donkeycar application is steering through the PCA9685. This can be observed while following the donkeycar user guide in the step of calibrating the car. Calibrating the donkeycar takes the plugged in channel and the bus, which are the same required options using the *Adafruit_9685* library. Every time the calibrate function is executed a new donkeycar instance is initiated. Therefore our driving function writes directly to the controller without the donkeycar instance. Nevertheless the donkeycar calibrate function is helpful for getting the PWM values at which the steering is full left, straight and full right. Using the other channel the same procedure can be used to get the PWM values for full throttle, zero and full throttle backwards. I shows the different PWM values observed while using the calibrate function.

TABLE I: PWM values

mode	value
left	460
center	380
right	290
forwards	500
stop	370
backwards	220

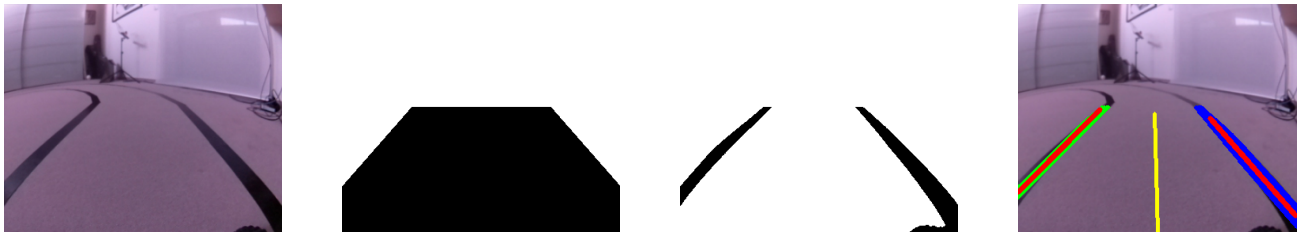
By using the boundary values each with the null value a respective linear equation can be set up.

Left	$pulse\_length = -4.4 * angle + 380$
Right	$pulse\_length = -3.6 * angle + 380$
Forwards	$pulse\_length = 1.4 * acceleration + 360$
Backwards	$pulse\_length = 0.6 * acceleration + 360$

These resulting equations are used in *driving_functions.py*. It can be used for steering and controlling the motor directly and is later used inside the python script for autonomous driving. The input for the steering function are steering angles reaching from -25 to 25 which are converted into degrees and into PWM signals. Using steering angles is easier for the human because they do not need to be abstracted. Similiar way is used for the motor control. Input values to the motor control function are percentages of the acceleration reaching from -100 to 100 which are again converted into PWM signals.

B. Lane Detection

Second subtask for driving autonomously is to detect the track lanes.



(a) Lane frame. (b) Stencil. (c) ROI frame. (d) Frame.

Fig. 1: Lane detection.

Video 1: Steering angle while driving.

Video 2: Dataset with control values.

Video 3: Dataset.

C. Autonomous Driving

Both subtasks merged together result in autonomous driving.

III. Donkeycar Autopilot

Although we decided against using the donkeycar library •**TODO:** (forgot why), we did experiment with it in an OpenAI gym environment called gym-donkeycar, which simulates a car that a donkeycar application can run on.

Donkeycar 2.5.8 comes with the ability to collect data and train a neural network built-in.

A. Data Collection

At each step the gym environment returns the image that the virtual car sees. The steering angle and throttle value are passed to the gym as a numpy array of length two by the donkeycar application. When recording drive footage, *json* files containing an image file name, steering angle, throttle value and other miscellaneous information are saved with the associated images in a folder. These folders can be used to train a model.

B. Training

Different model types are available under the *donkeycar.parts.keras module*. As the name indicates these model types are built with the Keras API on top of TensorFlow. The available types are:

Categorical takes an image as input and and has two categorical outputs for steering and throttle. The input is passed to a network with the following layers:

1) 5x5 Conv-ReLU, 24 filters, stride 2
2) 5x5 Conv-ReLU, 32 filters, stride 2
3) 5x5 Conv-ReLU, 64 filters, stride 2 or 3x3 Conv-ReLU, 64 filters, stride 1
4) 3x3 Conv-ReLU with 64 filters and stride 2 or 3x3 Conv-ReLU, 64 filters, stride 1
5) 3x3 Conv-ReLU, 64 filters, stride 1
6) Dense-ReLU, 100 outputs
7) Dense-ReLU, 50 outputs
8) Dense-Softmax, 15 outputs for steering and Dense-Softmax, 20 outputs for throttle

Linear takes an image as input and has two scalar outputs for steering and throttle. The input is passed to a network with the following layers:

1) 5x5 Conv-ReLU, 24 filters, stride 2

2) 5x5 Conv-ReLU, 32 filters, stride 2
3) 5x5 Conv-ReLU, 64 filters, stride 2
4) 3x3 Conv-ReLU, 64 filters, stride 1
5) 3x3 Conv-ReLU, 64 filters, stride 1
6) Dense-ReLU, 100 outputs
7) Dense-ReLU, 50 outputs
8) Dense-Linear, 1 output for steering and Dense-Linear, 1 output for throttle

IMU — takes an image and an IMU vector as input and has two scalar outputs for steering and throttle. The image is passed to a Linear network without layers 7 and 8, while the IMU vector is passed to a network with 3 Dense-ReLU layers with 14 outputs each. The outputs of both networks are concatenated and passed to a network with 2 Dense-ReLU layers with 50 outputs each and two separate Dense-Linear layers with 1 output for steering and throttle respectively.

Latent — takes an image as input and has two scalar outputs and an image output. This experimental model type uses convolutional layers to learn a latent vector and transposed convolutional layers to reconstruct an image from the latent vector as well as dense layers to produce the steering and throttle outputs from the same latent vector.

RNN — takes a sequence of images as input and has one 2D output for steering and throttle. The images are passed to a Linear network whose last Conv-ReLU layer is replaced with a 2x2 MaxPooling layer and the Dense-ReLU layer with 50 outputs is removed entirely. To make use of the sequence of images, each layer is wrapped inside a TimeDistributed layer, which applies the wrapped layers to each input. Two Long Short-Term Memory layers with 128 outputs followed by four Dense-ReLU layers with 128, 64, 10, and 2 outputs respectively complete the network.

3D — takes a sequence of images as input and has one 2D output for steering and throttle. The input is passed to a network with the following layers:

1) 3x3x3 3D Conv-ReLU, 16 filters, stride (1,3,3)
2) 1x2x2 3D MaxPooling, stride (1,2,2)
3) 3x3x3 3D Conv-ReLU, 32 filters, stride (1,1,1)
4) 1x2x2 MaxPooling, stride (1,2,2)
5) 3x3x3 3D Conv-ReLU, 64 filters, stride (1,1,1)
6) 1x2x2 3D MaxPooling, stride (1,2,2)
7) 3x3x3 3D Conv-ReLU, 128 filters, stride (1,1,1)
8) 1x2x2 3D MaxPooling, stride (1,2,2)
9) Dense-BatchNorm-ReLU, 256 outputs
10) Dense-BatchNorm-ReLU, 256 outputs
11) Dense, 2 outputs

Behaviour — takes an image and a behaviour vector as input and has two categorical outputs. The image is passed to a Linear network without layers 7 and 8, while the Behaviour vector is passed to a network with 3 Dense-ReLU layers with each layers outputs twice its inputs. The outputs of both networks are concatenated and passed to a network with a Dense-ReLU layers with 100 outputs followed by one with 50 outputs and two separate Dense-Linear layers with 15 outputs for steering and 20 outputs for throttle.

Localizer — takes an image as input and has two scalar outputs for steering and throttle and one categorical output for location. The image is passed to a Linear network which has an additional Dense-ReLU output layer for a location output with the number of outputs specified by the user.

IV. DAGGER

A. Description

DAGGER (Dataset Aggregation), developed by Ross et al. [2], is an iterative algorithm, which in each iteration i uses policy π_i to collect in dataset $\mathcal{D}_i$ state-action pairs $(s, \pi^*(s))$, where s is the state visited by the policy π_i and $\pi^*(s)$ is the associated action returned by an expert policy π^*. A classifier $\hat{\pi}_{i+1}$ is then trained on $\mathcal{D} = \mathcal{D}_1 \cup \cdots \cup \mathcal{D}_i$ (see Figure 2).

In practice this means an expert, in our case **•TODO:** (lane follower), takes control of the autonomous car and collects image-action pairs, where the action is a steering angle and a throttle value. A classifier is trained on the available data and used to collect new images, all of which are then labeled by the expert. Those new image-action pairs are combined with the old and used to train the next classifier. The process of data collection, expert labelling, and training is repeated until a satisfactory classifier has been trained.

1: Initialize $\mathcal{D} \leftarrow \emptyset$
2: **for** $i = 1$ **to** N **do**
3: Let $\pi_i = \beta_i \pi^* + (1 - \beta_i)\, \hat{\pi}_i$.
4: Sample T-step trajectories using π_i.
5: Get dataset $\mathcal{D}_i = \{(s, \pi^*(s))\}$ of visited states by π_i and actions given by expert.
6: Aggregate datasets: $\mathcal{D} \leftarrow \mathcal{D} \cup \mathcal{D}_i$.
7: Train classifier $\hat{\pi}_{i+1}$ on $\mathcal{D}$.
8: **end for**
9: **return** best $\hat{\pi}_i$ on validation.

Fig. 2: DAGGER algorithm

TABLE II: Results

iteration	distance travelled
1	x laps

Note, that due to the lack of data and therefore policies in the first iteration, we usually set

$$\beta_i = \begin{cases} 1, & \text{if } i = 1 \\ 0, & \text{else} \end{cases}$$

or

$$\beta_i = \begin{cases} 1, & \text{if } i = 1 \\ p^{i-1}, & \text{else} \end{cases}$$

where p is some probability, to directly utilize the expert as our first policy. Subsequent policies $\hat{\pi}_{i+1}$ are trained on expert labeled states visited by the current policy π_i or a combination of the current policy and the expert policy.

B. Implementation

We used a neural network, implemented in PyTorch, similar to the Linear network used by donkeycar to train the next policy on the expert labeled dataset. For details on the expert implementation see section •**TODO:** (no ml). We set $\beta_1 = 1$ utilizing the expert in the first iteration and $\beta_{2:n} = 0$ utilizing the trained policy in the remaining iterations.

C. Results

We measure distance travelled by the trained policy until the car veers off track. See table II for results.

V. Conclusion

References

References

[1] M. Abadi et al. "Tensorflow: Large-scale machine learning on heterogeneous distributed systems," arXiv preprint, 2016.

[2] S. Ross et al. "A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning", Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics, AISTATS 2011, Fort Lauderdale, USA, April 11-13, 2011