End-to-End Learning for Lane Keeping of Self-Driving Cars

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Abstract

In End-to-End Learning for Lane Keeping of Self-Driving Cars (2017) Chen and Huang present an alternative method for lane keeping in autonomous transportation. They argue that the traditional approach of decomposing the self-driving problem into image detection, path planning, and control logic can be replaced by a self-optimizing end-to-end learning solution. A convolutional neural network is fed images captured by a front view camera on the autonomous vehicle and outputs a steering angle. The limitations of the approach and further work is discussed.

1   Introduction

Autonomous vehicles need to be able to keep in lane to be able to navigate today's road infrastructure. In their paper Chen and Huang investigate the usage of a simple color camera for this purpose. Traditionally the problem is divided into a few sub-problems, including lane detection, path planning and control logic. They argue this approach is laborious, complex, and more prone to errors than a machine learning approach. In the paper they present a convolutional neural network which maps input images to a control signal directly. The neural network is a regressive solution to the steering problem. It attempts to learn the connection between an image and the dependent steering angle through gradual improvements on its estimations on the training data. Chen and Huang argue that the end-to-end optimization approach is a superior solution.

2   Implementation

The end-to-end approach utilizes *comma.ai*'s dataset of driving footage and data.[1] It consists of 7.25 hours of high-way driving. Before using the dataset, extensive preprocessing was done. The dataset contains a multitude of data, however only the images and the current angle of the steering wheel was of interest. The image-angle pairs were extracted. Video clips containing lane changes and turns were removed. Also driving at nighttime was not included. After preprocessing only 2.5 hours remained. About half an hour were used as the test set, while the remaining 2 hours served as the train set. As highways tend to be straight, only a fraction of the data contained footage of driving on curved roads. To ensure that the network would not tend to recommend driving straight even on curved roads, steering angles greater than 5 degrees in absolute value were up-sampled by 5. They use 3 convolutional layers, a flattening layer, 2 dropout layers and 2 fully connected layers. The convolutional layers are mainly for feature extraction and the fully connected ones for steering angle prediction. The dropout layers are there to prevent overfitting. The use of convolutional neural networks is appropriate when images are to be interpreted. This is not explicitly justified by the authors but is in widespread use in the scientific

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[1] https://github.com/commaai/comma2k19

community. The loss function is Euclidian loss. Due to the small dataset the network architecture is not the main concern of the article, it is more concerned with proving its usefulness for the task at hand.

3   Results

The performance of the ai-approach is not compared to the performance of the traditional-approach it is proposed to replace. However, the authors claim superior performance. The paper seems to serve mostly as a benchmark for improvements in future work. The model is evaluated on the difference between the outputted control signal and the human steering angle for each. The mean absolute error and the standard deviation is computed. From the very limited training set the model achieves a mean absolute error of 2.42 degrees on the test set. The standard deviation is 3.26 degrees. The authors indicate that the chosen evaluation metric is not entirely appropriate for this task.

4   Discussion

When evaluating the predictions on the individual frames the authors come across an issue. The neural network does its predictions on each frame independently, however steering a car is a continuous operation. This means that turning the wheel takes some time. The control signal will be able to react instantly to a turn, a discontinuous jump in steering angle. However, the human steering which serves as our target takes some time to turn the wheel to the appropriate angle. This means that an error is recorded for a few frames until the human catches up. In addition, the chosen metric does not impose a stricter punishment for drifting out of the lane for a small period than for small errors over a longer period. even though scenario 1 is unacceptable and scenario 2 is not. A better metric and some modelling of the physics of a car can mitigate these errors.

The message of the authors is that the proposed method must be regarded as an alternative to the traditional approach, with a possibility to become the favorable approach for lane keeping software in autonomous cars. Moreover, their main selling point is the reduction in manual labor required to create a working lane keeping system. They argue that the fewer components make for a more robust system compared to the traditional approach. Still there are several issues that need further investigation, which the authors intend to pursue in future work.

In my opinion the approach is promising, however there are some challenging issues that need to be addressed. Neural networks are known to be difficult to understand. It is hard, almost impossible, to decipher their decision process. The values of the different parameters do not have a clear, tangible meaning. However, the effect of the convolutional layers can be visualized, and the authors do this. From their examples it is apparent that the network identifies the road markings, without being explicitly engineered to do so. As an isolated system the machine learning approach seems to be working, but in the context of a fully autonomous car there are a lot more challenging scenarios that need to be explored. Much of regular day to day driving is not on mostly straight highways. There are poorly marked, unmarked or even wrongly marked streets which also need to be maneuvered. The paper does nothing to indicate the performance on such roads. It would be interesting to see how the system reacts to large errors, how it recovers. The authors argue that the fewer steps involved in the machine learning approach towards lane keeping make for better error handling, since there is less error propagation where an errors significance can amplify.

5   Conclusion

Chen and Huang introduce an end-to-end self-optimizing solution for lane keeping of self-driving cars. They propose to replace the traditional approach of decomposing the problem into image detection, path planning and control logic. The results are promising, and the paper is a first step towards the

development of self-driving cars using a convolutional neural network for lane keeping. However, there are several issues with the demonstrated solution, and there is a need of further research before it can be applied in production.

References

Zhilu Chen and Xinming Huang. 2017. *End-to-End Learning for Lane Keeping of Self-Driving Cars*. 2017 IEEE Intelligent Vehicles Symposium (IV), Redondo Beach, CA, USA.