Steering Wheel Angle Prediction for Autonomous Vehicles

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Abstract: Autonomous self-driving cars work based on the principle that the operation of the steering wheel is automated. The real-time video is analyzed and the the direction of the wheel is predicted from the input data. Changing and managing the velocity of the vehicle is done using a similar methodology too. This work discusses the development of a method to accurately predict the steering wheel angle with the aid of a sequence of images. These images consists of lane view pictures with less than ideal traffic present. The datasets considered for the work consists of about 63,000 such images. The respective steering angles are also provided as a set of numerals. The feature extraction and prediction is done by training an end-to-end Convolutional Neural Network on the input data viz. the image sequence and the respective steering wheel angles.

1. Introduction

Self-driving vehicles, also known as autonomous vehicles (AV), are vehicles that are capable of sensing their immediate environment and moving in a safe manner with minimal human input. Autonomous vehicles combine various sensors to perceive their surroundings. The data collected from these sensors and used to identify appropriate paths, obstacles on the path and the appropriate signage. There are several works engaging in the development of self-driving vehicles with varying degrees of success.One important aspect of an autonomous self-driving vehicle is its ability to correctly predict the steering wheel angle based on the input video from the vehicle's dash-cam. This is necessary for the vehicle to steer itself properly and to identify the scenarios in which it must take a turn and those in which it must drive straight.

This is an important component of an autonomous vehicle. Failure in developing this component properly will lead to multiple accidents and crashes resulting in the autonomous vehicle becoming unusable. This work describes the development of a Deep Learning model to accurately predict the steering wheel angle based on the input given. Development of a Convolutional Neural Network to train on a sequence of lane view images with corresponding steering wheel angles. Using the deep learning model to accurately predict the steering wheel angle when given a sequence of images. Demonstrating how the above technique would be vital in the development of a autonomous self-driving vehicle.

2. Related Works

E. Santana et al. [1] describes the development of an Agent that simulates the behaviour of a driver behind the wheel and decides the steering wheel movement by predicting the future events. This method illustrates the usage of a Recurrent Neural Network to train on the video data and give predictions on the movement of the vehicle. K. U. Kamath et al. [2] authored a paper which describes that with human steering angle as the limited training signal, the system improvises and automatically learns to detect the road visibility. Despite no explicit training for the detection of outline of the road, the system efficiently optimizes all processing steps simultaneously when compared to explicit decomposition of the problem.

P. J. Navarro et al. [3] authored a paper which describes that the complex decision-making systems used for autonomous vehicles or advanced driver assistance systems (ADAS) are being replaced by end-to-end (e2e) architectures based on deep-neural networks (DNN). DNNs can learn complex driving actions from datasets containing thousands of images and data obtained from the vehicle perception system. NVIDIA team consisting of

Fig. 1. Images from the Dataset

	Image	Angle	date
63795	63795.jpg	-9.880000	2018-07-01 18:05:35:29
63796	63796.jpg	-9.880000	2018-07-01 18:05:35:89
63797	63797.jpg	-9.880000	2018-07-01 18:05:35:128
63798	63798.jpg	-9.880000	2018-07-01 18:05:35:198
63799	63799.jpg	-9.880000	2018-07-01 18:05:35:255
63800	63800.jpg	-9.880000	2018-07-01 18:05:35:294
63801	63801.jpg	-9.880000	2018-07-01 18:05:35:353
63802	63802.jpg	-9.880000	2018-07-01 18:05:35:394
63803	63803.jpg	-9.880000	2018-07-01 18:05:35:461
63804	63804.jpg	-9.880000	2018-07-01 18:05:35:518
63805	63805.jpg	-9.880000	2018-07-01 18:05:35:558

Fig. 2. Structure of CSV File

Bojarski [4] et al, carried out a study to design an end-to-end learning of self-driving cars. They trained a convolutional neural network (CNN) to map raw pixels from a single front facing camera directly to steering commands. They found that this method was surprisingly accurate, without much training from humans the model managed to learn to drive in traffic on local roads some of which had lane markings while some did not as well as on highways.

N. Yadav et al. [5] from the University of Massachusetts Amherst Amherst MA propose a research work that describes that, using only steering angle as the training signal, deep neural networks can automatically extract features from the images to help understand the position of the car with respect to the road to make the prediction. Schmidt et al. [7] proposed a mathematical model that is able to predict the lane changes by utilising the angle at which the steering wheel is inclined. The model uses combination of data from three different sources: a) driver behaviour b) sensor data c) automobile telemetry. Different algorithms where used to combine the data from the above sources and provide a prediction. Some of the algorithms were, Hidden Markov Models, Neural Networks etc. Finally all the models were combined and the prediction was used to assist the driver in performing the lane change.

3. Existing Work

The usage of Recurrent Neural Networks is popular in research trying to predict the steering wheel angles. These models make use of only the steering wheel angles which vary according to time. This forms a time series on which the Recurrent Neural Network is trained. These models are trained to make prediction without any further information such as data from the sensors or cameras etc. Some models take the classic approach and employ the usage of complex algorithms and use obstacle detection sensors to predict the steering wheel angle. These models are not explicitly trained and are able to optimize themselves for any given road conditions. Recent studies have explores the usage of end to end Deep Neural Networks to train on the lane images and predict the steering wheel angles. These models use Convolutional Neural Network to extract the features from the lane images and train on those features to make the predictions. Some mathematical models exist that are able to predict future lane changes by analyzing the current state of the steering wheel. Some of the mathematical models where Hidden Markov models, Neural Networks etc.

4. Dataset

The dataset used is publicly available at the author's GitHub repository [6]. The dataset is a 30fps video of around 25 minutes which makes up to approximately 45,000 images. The width and height of the images are 455 and 256 pixels respectively with Bit Depth as 24. These are lane view images, taken from a four-wheeler's dashboard, that simulate the view from an autonomous self-driving vehicle. The images were taken in a situation of little to no traffic density. The datasets are also accompanied by a CSV file which contains, the name of the image, corresponding steering wheel angle, and the timestamp relating to the time at which the image was taken (ref. Fig. 2). The images were captured around the regions of Rancho Palos Verdes, California and San Pedro, California. The first 80% (approx. 20 min) of total images is taken for training and remaining 20% (approx. 5 min) of the images is taken for testing purpose. An example can be viewed in Fig. 1. There are other publicly available video datasets with long duration.

5. Methodology of Proposed Work

5.1. Data Pre-processing

The ratio of train test data split is 4:1. Train and test data is separated into batches initially. The SciPy library for python is used to extract the images. The images extracted from the dataset are first subjected to resizing. The images of initial dimensions 455 x 256 are resized to a width of 200 pixels and a height of 66 pixels. Setting a uniform size to all the images is a crucial part of the training process of a Convolutional Neural Network. Next the data obtained are subject to normalization. Since pixel data is in the range of 0 to 255, all the data points are divided by 255 to limit the range between 0 and 1. It is used to maintain the general distribution and ratios in the source data while also keeping values in the same scale. It also decreases the training time by making the calculations made simpler and more effective. The steering angles are converted to radian by multiplying the degrees with factor pi/180 in order to reduce the range and computation easier.

5.2. End to End CNN Architecture

Convolutional Neural Networks (CNNs) were used to convert raw pixels from a front-facing camera to self-driving car steering signals. With this sophisticated end-to-end technique, the system learns to steer, with or without lane markers, on both local roads and highways, with minimal training data from people. The technique can also work in areas where there is no obvious visual direction, such as parking lots or dirt roads. With only the human steering angle as the training signal, the system is trained to automatically acquire the internal representations of key processing tasks, such as detecting useful road characteristics. To detect the outline of roadways, for example, we do not need to explicitly train it. End-to-end learning improves performance and reduces the size of the system. Internal components self-optimize to maximise total system performance rather than human-selected intermediate criteria, such as lane detection, resulting in better performance.

Such criteria are clearly chosen for ease of human understanding, but they do not guarantee maximum system performance. Because the system learns to solve the problem with the fewest amount of processing steps possible, smaller networks are possible. Figure 3 depicts the architecture of the model which is used, further we added dropout layers in between the fully connected layers to prevent overfitting and to increase the accuracy. First RGB channelled images are resized to 66 x 200 and normalized. The architecture has 5 convolutional layers followed by 3 fully connected layers with dropout layers in between 2 fully connected layers. The number of kernels is kept increasing for convolutional layers. Mean Square Loss plus L2 regularized loss is used to avoid overfitting. Adam optimizer is used to update network weights with $10\hat{(}-4)$ as learning rate. The model was trained for 30 epochs as the test loss was around 0.14 at the end of the training.

6. Results and Discussion

At the end of 30th epoch the train loss was around 0.14 which is pretty good for the CNN model. With help of OpenCV, the steering wheel image is turned by predicted angle with respective to each and every frame. Last 30% of the 45,000 images is used as test data. Figure 4 depicts the predictions obtained from the model for the testing data. A sample of the log captured while running the model can be seen in Fig. 6, deviations of predicted steering angles from actual steering angles for each and every frame is displayed.

The deviations were minimal for most of the frames. The trained model is able to make turns according to the roads even at the sharp corners. More work is needed to increase the network's robustness, discover techniques to verify it, and better visualisation of the network's internal processing stages. This end-to-end CNN model

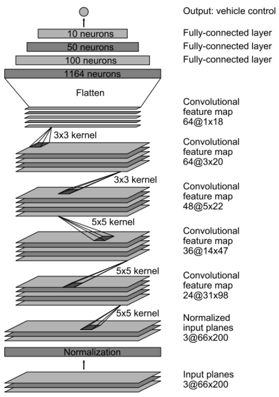


Fig. 3. Architecture of the CNN

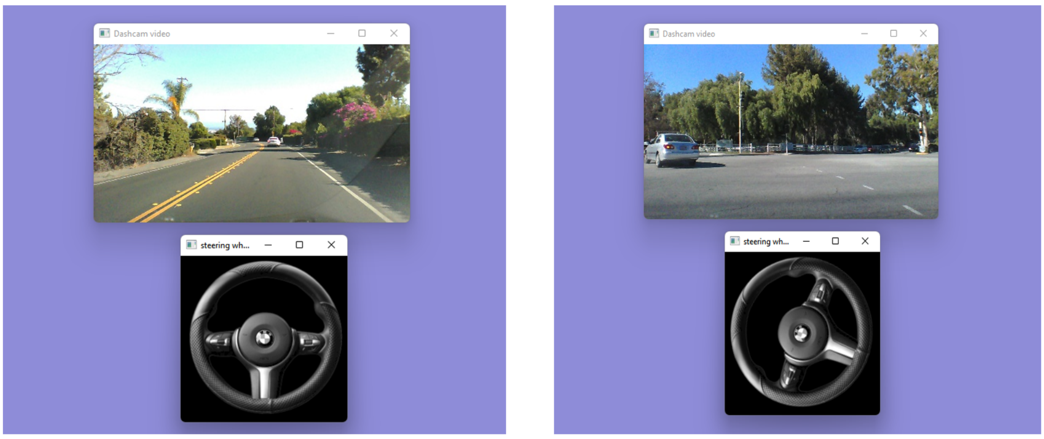


Fig. 4. Predictions from the model

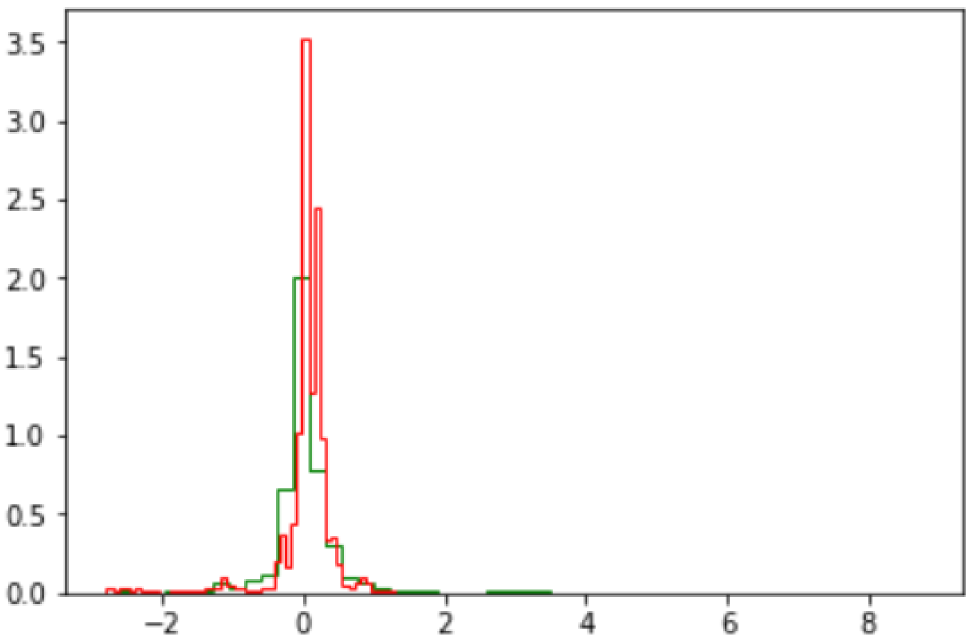
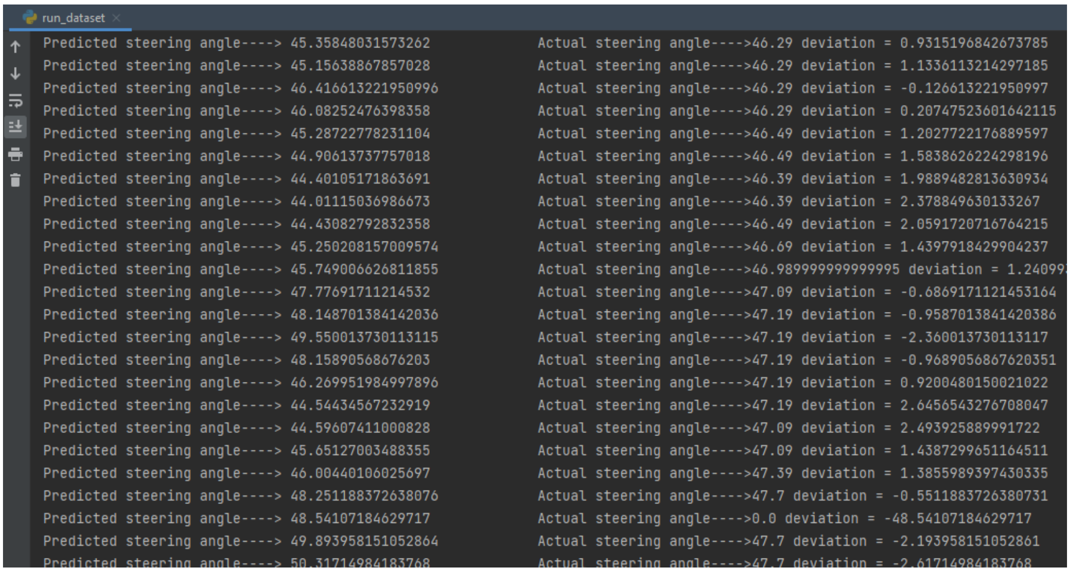


Fig. 5. Train and Test steering angles



```
run_dataset
Predicted steering angle----> 45.35848031573262        Actual steering angle---->46.29 deviation = 0.9315196842673785
Predicted steering angle----> 45.15638867857028        Actual steering angle---->46.29 deviation = 1.1336113214297185
Predicted steering angle----> 46.416613221950996       Actual steering angle---->46.29 deviation = -0.126613221950997
Predicted steering angle----> 46.08252476398358        Actual steering angle---->46.29 deviation = 0.20747523601642115
Predicted steering angle----> 45.28722778231104        Actual steering angle---->46.49 deviation = 1.2027722176889597
Predicted steering angle----> 44.90613737757018        Actual steering angle---->46.49 deviation = 1.5838626224298196
Predicted steering angle----> 44.40105171863691        Actual steering angle---->46.39 deviation = 1.9889482813630934
Predicted steering angle----> 44.01115036986673        Actual steering angle---->46.39 deviation = 2.378849630133267
Predicted steering angle----> 44.43082792832358        Actual steering angle---->46.49 deviation = 2.0591720716764215
Predicted steering angle----> 45.250208157009574       Actual steering angle---->46.69 deviation = 1.4397918429904237
Predicted steering angle----> 45.749006626811855       Actual steering angle---->46.989999999999995 deviation = 1.24099
Predicted steering angle----> 47.77691711214532        Actual steering angle---->47.09 deviation = -0.6869171121453164
Predicted steering angle----> 48.148701384142036       Actual steering angle---->47.19 deviation = -0.9587013841420386
Predicted steering angle----> 49.550013730113115       Actual steering angle---->47.19 deviation = -2.360013730113117
Predicted steering angle----> 48.15890568676203        Actual steering angle---->47.19 deviation = -0.9689056867620351
Predicted steering angle----> 46.269951984997896       Actual steering angle---->47.19 deviation = 0.9200480150021022
Predicted steering angle----> 44.54434567232919        Actual steering angle---->47.19 deviation = 2.6456543276708047
Predicted steering angle----> 44.59607411000828        Actual steering angle---->47.09 deviation = 2.493925889991722
Predicted steering angle----> 45.65127003488355        Actual steering angle---->47.09 deviation = 1.4387299651164511
Predicted steering angle----> 46.00440106025697        Actual steering angle---->47.39 deviation = 1.3855989397430335
Predicted steering angle----> 48.251188372638076       Actual steering angle---->47.7 deviation = -0.5511883726380731
Predicted steering angle----> 48.54107184629717        Actual steering angle---->0.0 deviation = -48.54107184629717
Predicted steering angle----> 49.893958151052864       Actual steering angle---->47.7 deviation = -2.193958151052861
Predicted steering angle----> 50.31714984183768        Actual steering angle---->47.7 deviation = -2.61714984183768
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Fig. 6. Log captured while running the model

can be implemented along with lane detection, pedestrian detection models to assist in decision making for self-driving cars.

7. Conclusion

This project shows that Convolutional Neural Networks can learn the whole task of lane and road following without manual segmentation by the way of detection of road or lane markings, semantic abstraction, path planning, and control. During training, the system learns to detect the outline of a road, for example, without the use of explicit labelling. A tiny amount of data from less than a hundred hours of driving was enough to teach the automobile to operate in a variety of situations, including highways, local and residential roads, and sunny, cloudy, and wet weather. From a sparse training input, the Convolutional Neural Network is able to acquire relevant road features (steering alone).

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