

Predicting a vehicles speed using dashcam footage

A deep learning approach

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Machine Learning using Matlab
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Table of content

- 1 Motivation, data collection and initial assumptions
- 2 Preprocessing and optical flow
- 3 Method selection and architecture
- 4 Fine Tuning of the model

The “comma ai speed challenge”¹

Motivation

- Here are some motivational words needed

Data collection:

- “comma ai speed challenge” provides two videos:
 - Train video: 24000 frames, shoot at 20 frames per second, including ground truths
 - Test video: 10798 frames, shoot at 20 frames per second, no ground truths, used to applications
- Split train video after 80% with hard cut off (ability the generalize), to get train and test datasets

Initial assumptions

- Use mean squared error (MSE) as a performance measure
- How to evaluate a prediction? Assumptions:
 - $MSE \leq 10$: good
 - $MSE \leq 5$: better
 - $MSE \leq 3$: correct

¹<https://github.com/commaai/speedchallenge>

Preprocessing

- Frame size of $(640, 480, 3)$ pixels
- Cut off last 60 pixels, to remove black frame inside the car
- Sample down the frame to half its size, due to computational limitations

IMAGES with arrows are needed

Optical flow using “Farneback pyramid method” [2]

- Global method to solve the optical flow equation

$$\partial_x f \cdot V_x + \partial_y f \cdot V_y + \partial_t f = 0$$

for an image sequence $(f_t)_t$ with $f_t : \Omega \rightarrow \mathbb{R}^3$, for all t , and the (dense) flow field $V : \Omega \rightarrow \mathbb{R}^2, \omega \mapsto (V_x(\omega), V_y(\omega))$.

- Uses a downsampling pyramid, to solve the equation for different resolutions of the image
- Parameters for the Farneback method

pyramid levels := 3

pyramid scaling := 0.5

window size := 6

pixel neighborhood size := 5

SD of the gaussian filter := 1.1

- Result: **Flow field with (160, 105, 3) pixels**

Visualization of the flow field

- Flow field is a two-dimensional vector field
- RGB representation via
 - Transform flow field into polar coordinates $(V_x, V_y) \rightarrow (r, \varphi)$
 - Normalize magnitudes r for third channel
 - Values of the second channel are set to 255
 - Multiply angle φ by factor $\frac{180}{2\pi}$ for first channel
- Sample down the size again, to speed up the training

IMAGE REQUIRED

Convolutional neural network and initial architecture

Method selection

- Speed prediction is a **non-linear regression** task \rightsquigarrow Neural network
- Use convolution layers to perform feature extraction \rightsquigarrow **convolutional neural network** (CNN)

Initial architecture

- Paper of NVIDIA work group [1] of a CNN for self-driving cars
- Enough complexity and layers to handle the task and lots of possibilities to fine-tune it

IMAGE OF THE MODEL

- Initial results with the raw model: MSE of under 3 on the training set and around 18-20 on the testing set
 \Rightarrow Improvements needed

Batch Normalization, Dropout layers and pooling

- Test

Literature I



Mariusz Bojarski et al. “End to End Learning for Self-Driving Cars”. In: (Apr. 2016). URL: <https://arxiv.org/pdf/1604.07316v1.pdf>.



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