Dynamic Risk Assessment for Vehicles of Higher Automation Levels by Deep Learning

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Introduction

- Stereo cameras are widely used in cars nowadays
- present a novel approach for the dynamic risk assessment of driving situations based on images of a front stereo camera using deep learning
- Trained a Convolutional Neural Network (CNN) with supervised learning to derive the risk of a driving scene
- This functionality can be used as a part of vehicles of higher automation levels.

CNN Network structure

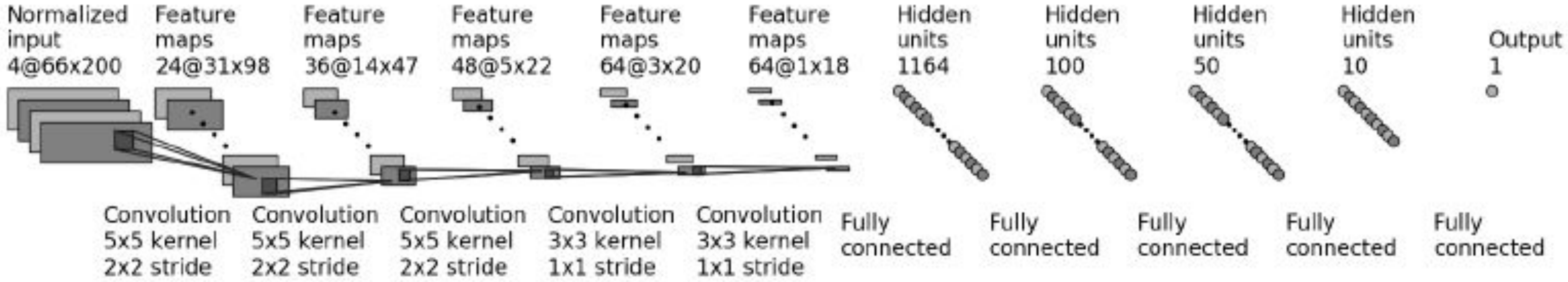

Fig. 1. The architecture of our neural network for risk estimation in driving scenarios

Simulation Environment

- A great amount of training data was required
- Challenging to create this amount of data in a real driving environment
- Environment needs to be large and random enough to be representative for a real environment
- Grand Theft Auto – V: With more than 500 vehicle models, urban and countryside road networks, and random actions of pedestrians and other drivers
- The data that extract from this game system is the valid data for the object classification algorithms.

Risk Metric Calculator (RMC)

- Determine the ground truth values for the dynamic risk assessment
- RMC used in this work is the reciprocal of the time headway metric
- Counting the least number of empty cells between one vehicle and another vehicle and dividing that distance by the current speed
- The higher the value of the metric, the higher the risk of the current driving situation
- The RMC considered the closest vehicle only
- A constant speed, no turning movement and target vehicle will not move at all

$$time\_headway = \frac{distance}{subject\_velocity}$$

Fig. 4. Left: Uncritical scene (0) — Right: Critical scene (0.21)

Training Progress

- 106,170 data points the training
- 70 % of the data was used for training,
- 10 % for validation
- 20 % was used for final testing.
- Training was performed for 30 epochs
- Batch size of 10

Results

- Minimize the mean squared error between true and predicted risk values
- Mean squared error = training average error
- Training error was steadily decreasing
- Network was able to learn an estimation of risk from the provided input data

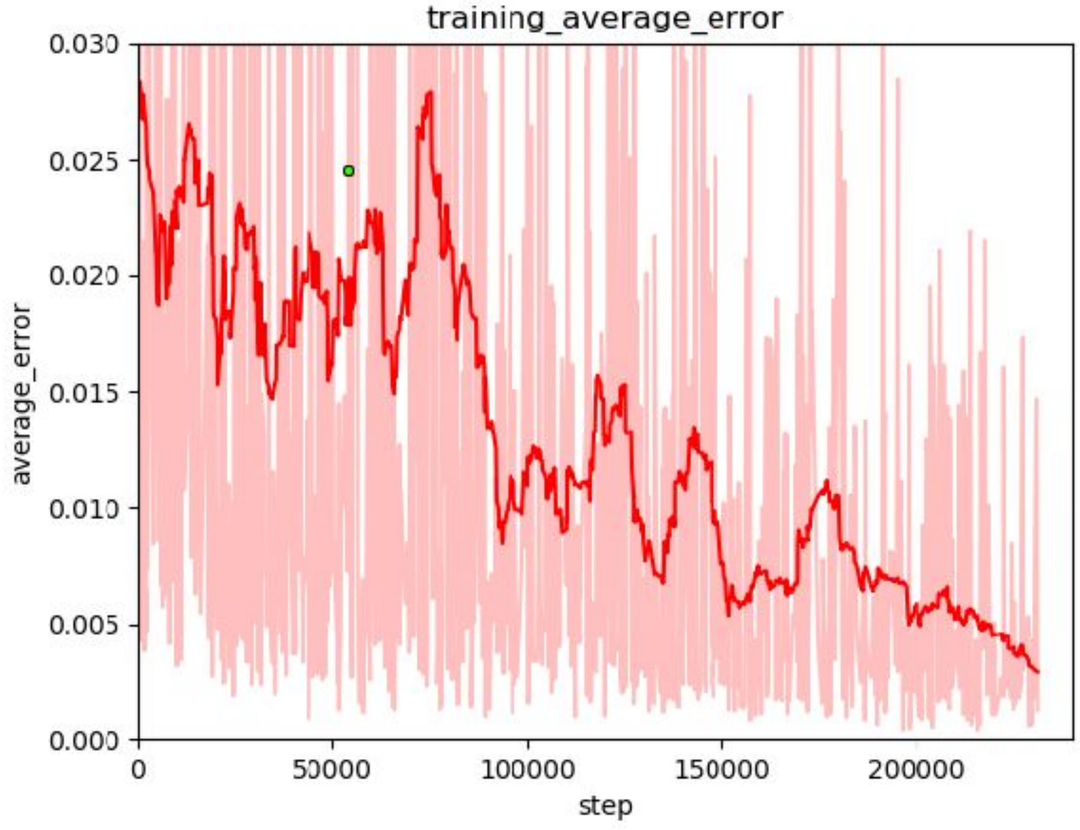

Fig. 5. Training Average Error

Results

- Monitored the validation error
- After approximately 15 epochs, the validation error started to increase.
- Optimal point to stop training
- The testing average error we achieved over all test data was 1.47%.

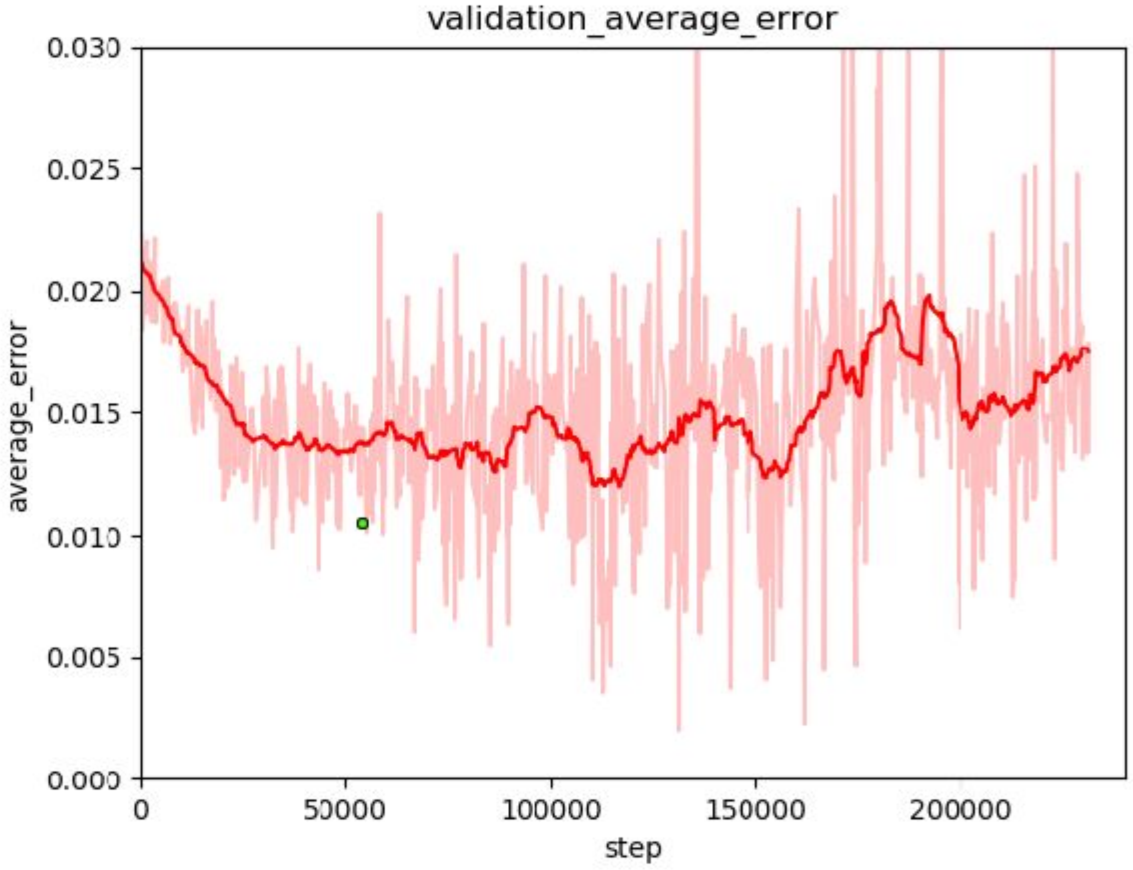

Fig. 6. Validation Average Error

Results

- Time headway value of 1.5s
- 106170 situations contains 76789 critical driving situations.
- CNN classified 67.052 correctly.
- The accuracy is 72.87%.

	Actual Critical Situation	Actual Uncritical Situation
Predicted Critical Situation	67052 (63,16 %)	19069 (17,96 %)
Predicted Uncritical Situation	9737 (9,17 %)	10312 (9,71 %)

Table 1. Confusion Matrix of the CNN

Results

A major reason for the bad performance of the network: The view of the camera did not perfectly match the area that the RMC considered in the calculation

Fig. 7. Left: Value from RMC: 0.36 Value from CNN: 0.38 — Right: Value from RMC: 0.75 Value from CNN: 0.39

Thinking

- Not Accepted.
- A novel approach for the dynamic risk assessment from images.
- Accuracy is only 72.87%.
- Need to transferred from the simulation environment to a real environment.

Discussion

- The solution show that the integrity of the developed approach is still far from what can be considered as usable in a safety-critical context. The accuracy of the that deep learning model is 72.87%. Any ideas to improve that accuracy?

Thank you！