UC San Diego

Estimation on vehicle motion based on vision

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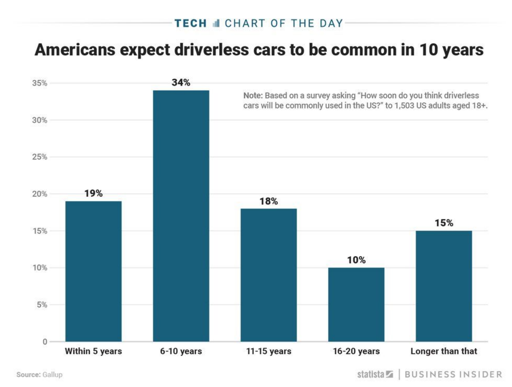
Introduction

Why estimating vehicle motion?

- ✔ Self-driving as a promising new technology
- ✔ Developments made over the years
- ✔ Existing various optical flow estimation algorithm



Autonomous driving shows great potential
Many industries has yielded promising results

Uber's self driving taxi

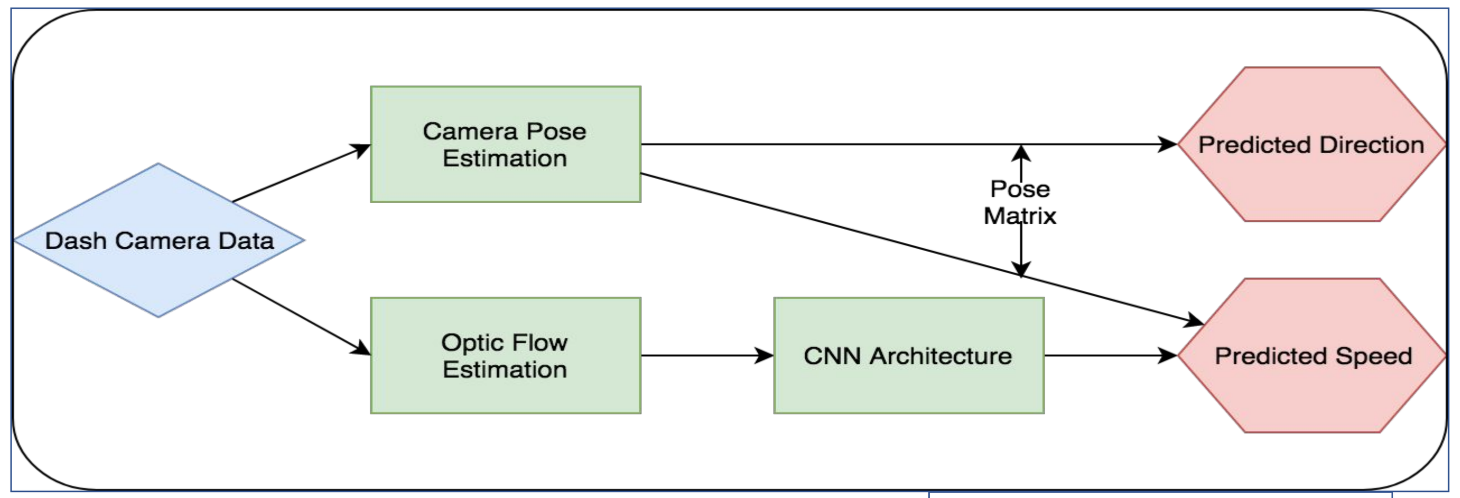
IN 2017, waymo reported only 63 driver engagements in 350 thousand miles of driving.

Our Goal

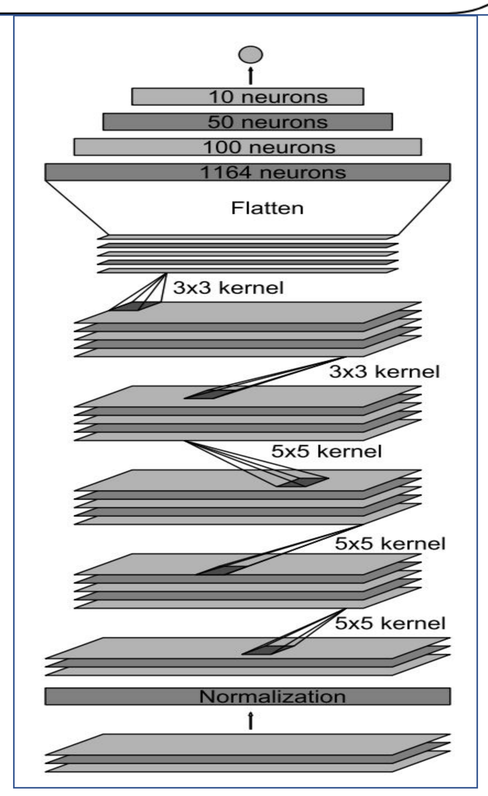
- Currently there are many algorism regarding optical flow in self driving.
- We want to improve classical methods so that it is more resistant to noise caused by weather and other environmental issues.

We want to compare algorithms that can estimate speed and vehicle direction

Methodology



CNN architecture
The network has about 27 million connections and 250 thousand parameters.



Input

- KITTI dataset with ground truth
- Stimulation data with ground truth
- Self-recorded dash video

Methodology Comparison

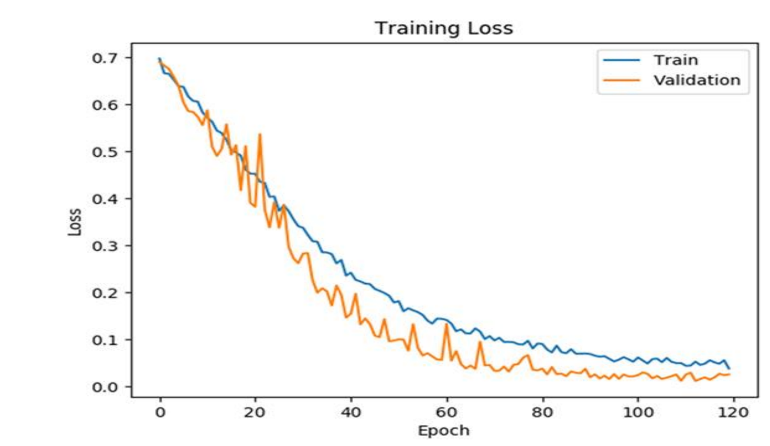
	Methodology	Estimate direction	Estimate speed	Accuracy on speed	Robustness w/ condition	Num. of Layers
Algorithms to detect vehicle motion with dash camera	Sparse optic flow (Forward wrapping)	Yes	No	N/A	Good weather No self-motion object	N/A
	Sparse optic flow (Lucas-Kanade Optical Flow)	Yes	No	N/A	Good weather Less self-motion object	N/A
	Dense optical flow (Sublinear Optical Flow Algorithm)	Yes	Low error	MSE: Testing:6.6627 Training:4.3672	High resolution data required	250 k parameters
	Dense optical flow w/ pose matrix estimation	Yes	Minimized error	MSE: Testing:5.5178 Training:2.4753	Consecutive and High resolution data required	250 k parameters

Input parameters: *Pose estimation, optical flow, speed estimation and direction estimation of the vehicle*

Data Set	Pose Estimation	Optical Flow	Speed Estimation	Direction Estimaton
KITTI	Yes	No	Yes	N/A
SimCity Simulation	Yes	Yes	Yes	Yes

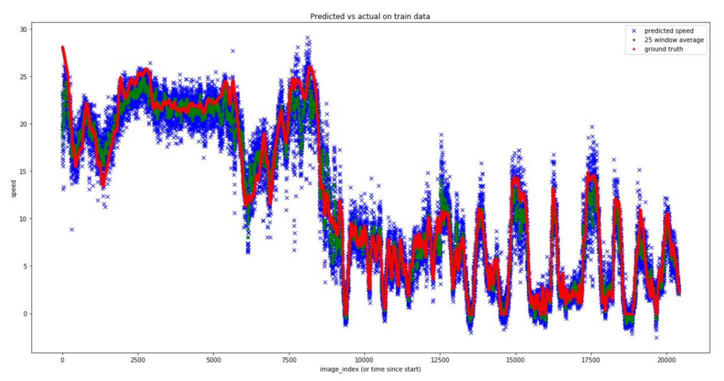
Result & Discussion

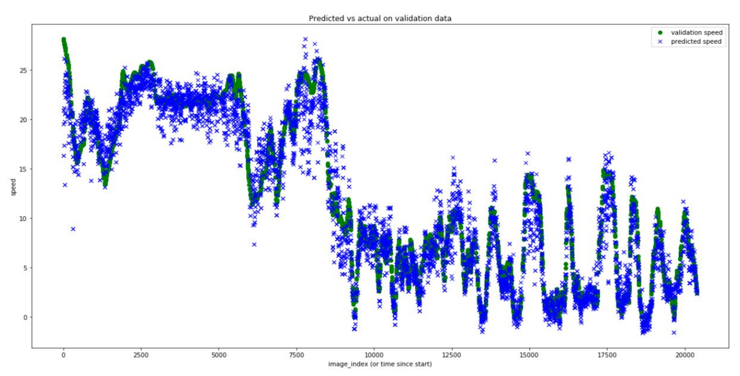
Benchmark:

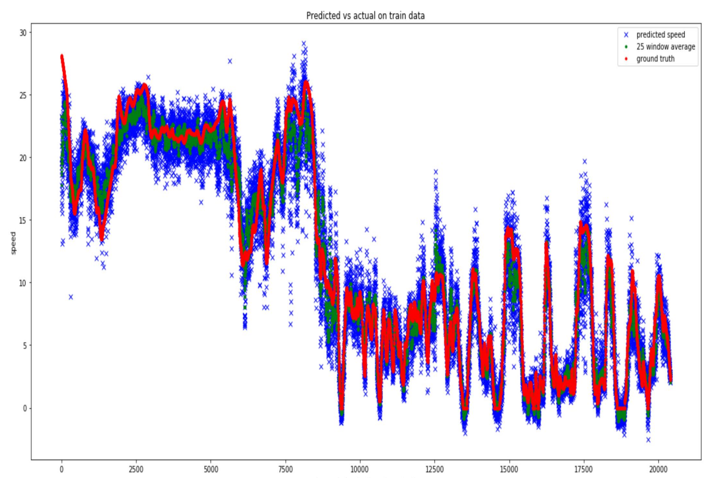


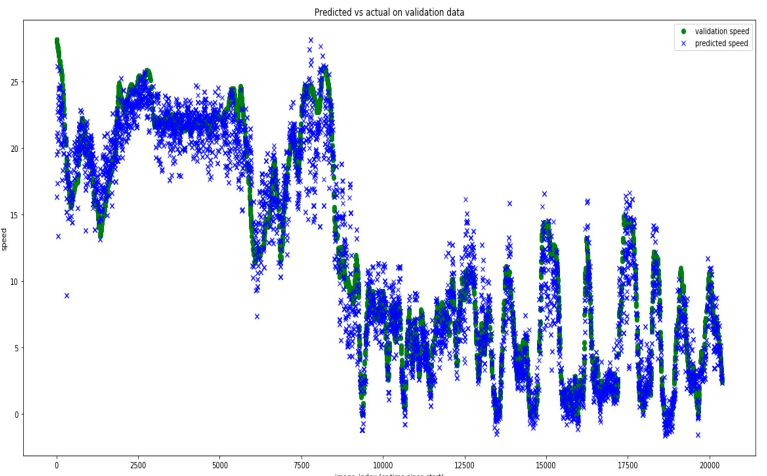
Train

Validation









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