Automatic Wheel Alignment via Machine Learning

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Gradient Descent

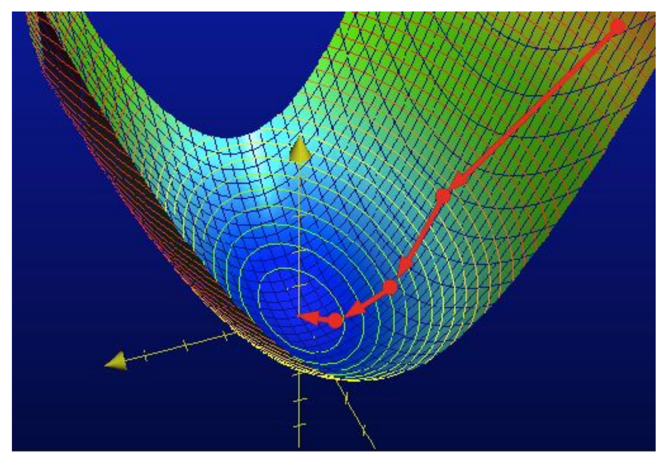
CONCEPT

- Minimize cost by iteratively stepping down gradient
- Cost function: “Minimize prediction error”

  $J = | x^{+}_{model} - x^{+}_{measured} |_2^2$

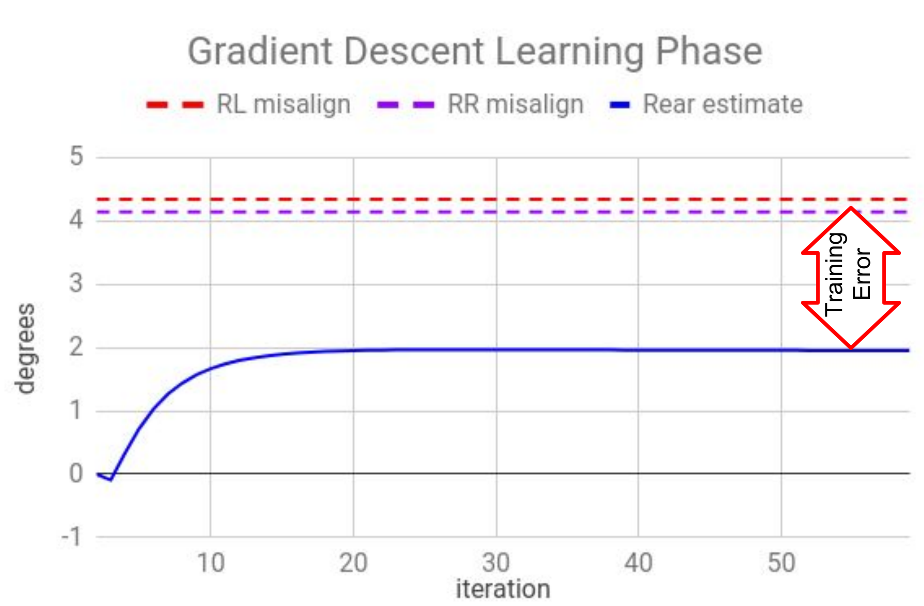
- Update: $\hat{\delta}_{misalign} \leftarrow \hat{\delta}_{misalign} - \eta \nabla_u J$

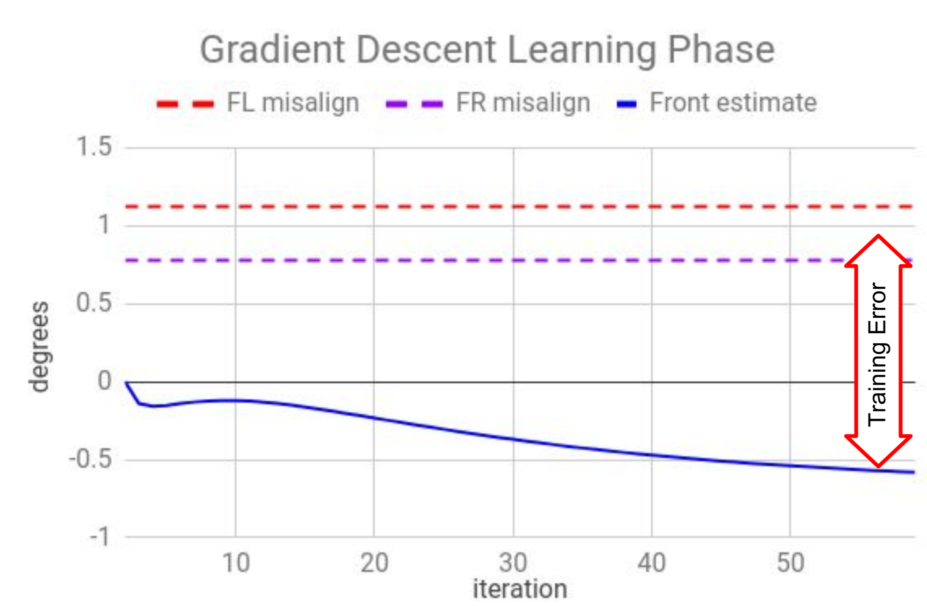
  Note: used linearized model to compute gradient

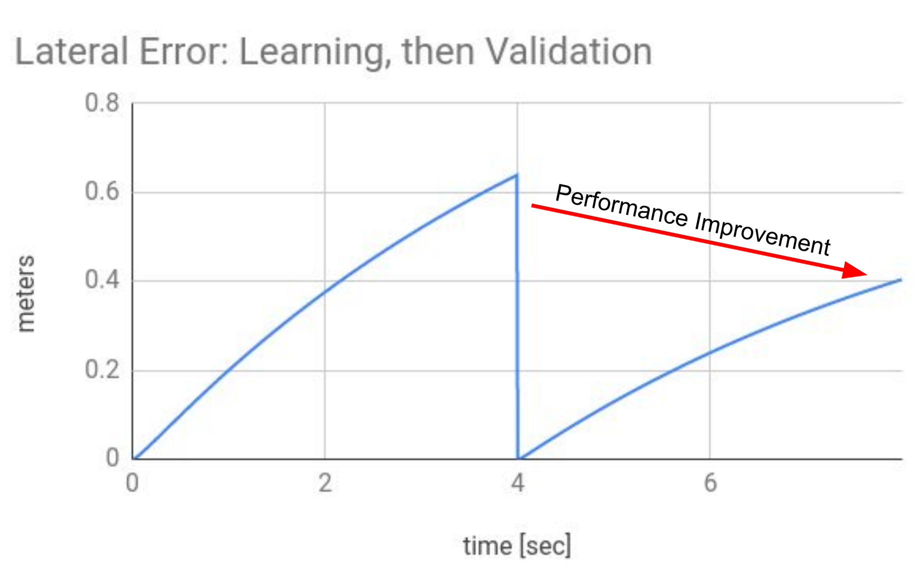


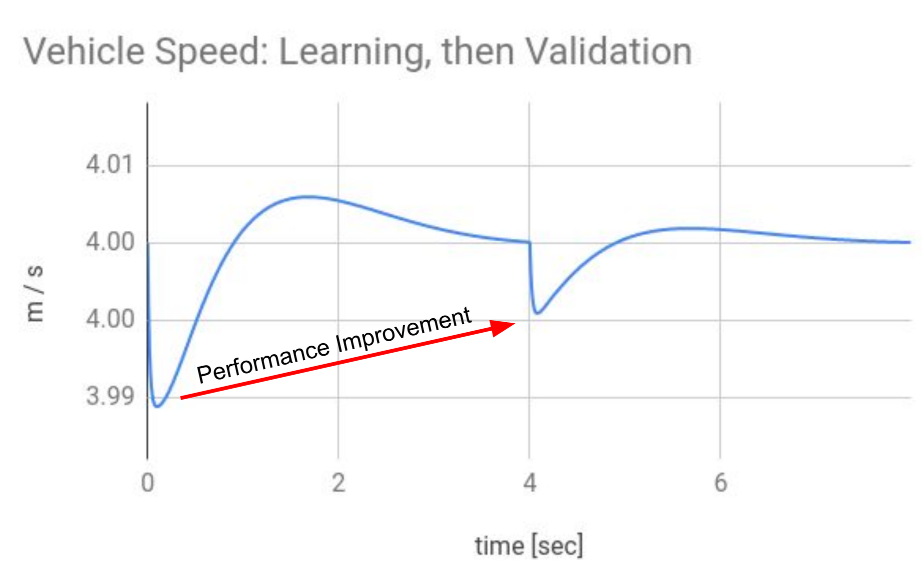
RESULTS & ANALYSIS

- Linearized model lumped left & right wheels, giving only two estimates
- Cost function may have local minima; significant error often remains
- Path-following performance typically shows improvement
- A typical experiment’s results below :







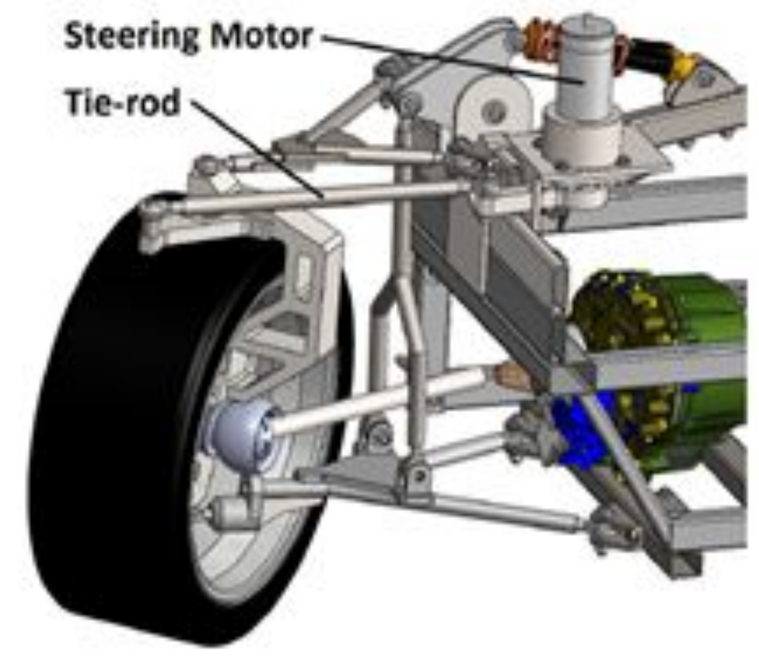


Motivation

A vehicle’s wheels must be aligned, such that steering angles are accurately commanded and measured.

Misalignment leads to:

- Tire wear
- Inefficiency
- Inaccurate control



Most vehicles’ wheels are aligned by manual hardware adjustment, but research platforms like X1 (see CAD diagram) and future commercial vehicles may be aligned in software.

Problem Definition

This project aims to demonstrate the feasibility of online automatic wheel alignment for vehicles via machine learning techniques including Gradient Descent and Value Estimation.

The experiments and results presented here use a high-fidelity nonlinear 4-wheel-steering vehicle model in lieu of experimentally measured data:

$$\text{state } x^{+} = F_{\text{NL model}} (\text{state } x^{0}, \text{command } u, \Delta t)$$

Experimental Procedure

0. Setup: Initialize simulated vehicle state, path, & four random misalignment angles $\delta_{misalign}$
1. Learning Loop :
   a. Simulate state forward using $\delta \mathrel{+}= \delta_{misalign}$
   b. Update misalign estimate $\hat{\delta}_{misalign}$ (gradient descent & value estimation)
2. Validation Loop :
   a. Simulate state forward using $\delta \mathrel{+}= \delta_{misalign} - \hat{\delta}_{misalign}$
3. Analyze $\hat{\delta}_{misalign}$ and path following performance metrics

Value Estimation

CONCEPT

- Maximize reward by choosing states with greatest value
- Reward function: $R = - | x^{+}_{model} - x^{+}_{measured} |_2^2$
- Mitigate discretization by function approximation (parabolic regression)

	-1.5°	-1.0°	-0.5°	0	0.5°	1.0°	1.5°
FR	-25	-15	-10	-1	-10	-15	-20
FL	-15	-10	-1	-10	-15	-20	-25
RR	-20	-15	-10	-1	-10	-15	-20
RL	-30	-25	-20	-15	-10	-1	-10

numbers for concept, not learned data

RESULTS & ANALYSIS

- Random exploration of candidate states sometimes leads to non-convergence
- Flat reward plateau → best correction angle is difficult to distinguish
- Path-following performance typically shows improvement
- A typical experiment’s results below :