Road To Reliability: Optimizing Self-Driving Consistency With Real-Time Speed Data

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Rationale

Why is Autonomous Driving Important?
✓ Self-driving cars can reduce human fatalities
✓ Accurate driving requires fast computation on edge devices
✓ Worst-case performance must be safe

Why does Self-Driving need HPC?
✓ For on-road driving, extremely large data sets required
✓ Fast computation needed for accurate inferencing

Reproducing End-to-end Principles
All data collected from human driving and Training a CNN [1]

End-to-End Outcomes
✓ Education/Reproducibility: Extensive documentation of project
✓ Troy: reproducible artifact
✓ Educational module for classrooms
✓ Testbed for Improvements: End-to-end compatibility with additional sensors
✓ Connection to Chameleon’s Chi@Edge
✓ Low cost; fast experimentation

Research Question
How can real-time speed data improve self-driving consistency?
✓ Problem: Comparing models is hard because of inconsistent speed
✓ Different battery life = different speed
✓ Performance varies on different surfaces

Proposed Solution

KerasVelocity Model
✓ Collect data with encoder speed
✓ Model predicts velocity instead of throttle

KerasLinear Model
✓ Model predicts throttle percentage based solely on image input

Expected Results:
✓ Model performance should be independent of battery percentage
✓ Improved performance on different surfaces compared to control
✓ Model should learn to be more cautious: less errors

Autonomy Score: 1 - (number of errors / number of laps)

Autonomy shows how well models could complete laps without errors. If no successful laps completed or if score below 0, autonomy considered to be 0

Completed Laps

Successful laps are full laps w/o error. Linear model made 0 successful laps on the Waveshare track in trials 2, 3, and 5

Errors

Errors defined as both wheels completely off the track or stuck for over 5 seconds. Velocity model made no errors on the normal track

Conclusion and Future Work

Default Track:
✓ Velocity autonomy marginally better than Linear (1.6%)
✓ Velocity makes marginally fewer errors (0 vs. 3)
✓ During successful laps, Linear drives 2.11 times faster than Velocity

Waveshare Track:
✓ Velocity autonomy 473% better than Linear
✓ Velocity makes 7.27 times fewer errors than Linear
✓ During successful laps, Linear drives 2.85 times faster than Velocity
✓ These results show that a velocity-dependent model is better suited for safety in autonomous driving
✓ As Future Work, more accurate encoder, testing on more surfaces. Calculate the trade off between speed and accuracy