Learning From Real-World Trajectories: A Hybrid Genetic Algorithm and Reinforcement Learning Approach for Vulnerable Road User Model Calibration

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Introduction

- Microscopic simulation models require accurate calibration to reflect real-world dynamics.
- Vulnerable road user (VRU) model calibration is challenging due to:
  - Complex interactions and behaviors.
  - Mode-specific interactions.
  - Diversity in infrastructure and the existence of shared spaces.
- Existing calibration methods, relying solely on numeric loss functions, often fail to capture realistic, human-perceived behavior.

Goals

- Introduce a calibration methodology to systematically adjust model behavior to include expert opinion:
  - Match model output with expected behavior.
  - Be reproducible across different models and platforms.
- Develop a hybrid genetic algorithm (GA) plus reinforcement learning (RL) calibration framework with human-in-the-loop preference modeling.

Dataset

Third-generation simulation (TGSIM):[1]

- Location:
  - Washington, DC, Foggy Bottom area.
  - Intersection of 1st Street NW and 23rd Street NW.
- Location characteristics: High VRU volume near George Washington University campus and Washington, DC, Metro station.
- Analysis: Pedestrians and bicyclists included.

TGSIM can be accessed through this link.[1]

https://urldefense.proofpoint.com/v2/url?u=https-3A__catalog.data.gov_dataset_-3Fq-3DThird-2BGeneration-2BSimulation-2BData-26sort-3Dviews-5Frecent-2Bdesc-26publisher-3DFederal-2BHighway-2BAdministration-26organization-3Ddot-2Dgov-26ext-5Flocation-3D-26ext-5Fbbox-3D-26ext-5Fprev-5Fextent-3D&d=DwIFAg&c=euGZstcaTDllvimEN8b7jXrwqOf-v5A_CdpgnVfiiMM&r=lGbI8AlAH_hHOjqaSFU1IBw02pDmmapIAZXRiFFieh0&m=5jzSPOy9MUpOto-YIDDpe5zpw9yUrHaDigD28A-PIlLKLdEOFZS2zfwlDSk_07v0&s=1aFEnFdpeSdVBPtgynxedE9ilOK6YM3jLXBeT85WYj8&e=

Methodology

To simulate user movement, two models were utilized:

- Social force model (SFM):[2]
  - Models motion via attractive (goal-oriented) and repulsive (collision-avoidance) forces between agents and obstacles.
- Prospect theory (PT)-based model:[3]
  - Provides a framework to capture decisionmaking under uncertainty.
  - Assumes gains and losses influence decisionmaking differently.

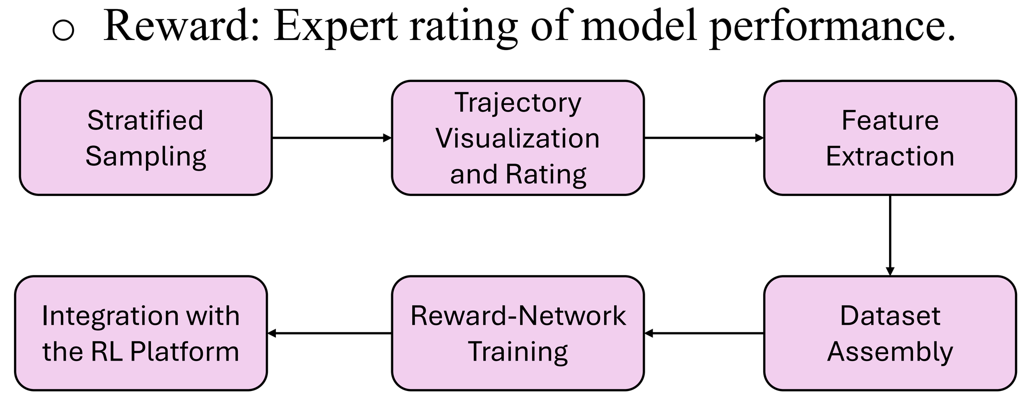
A two-step calibration approach is proposed:

- Step 1: Calibrating using GA, minimizing discrepancy between simulated and observed speeds.

$$f(\theta_i) = 1 \Big/ \left[1 + \sum\left(v_i^{Observed} - v_i^{Predicted}(\theta_i)\right)\right]$$

Where $v_i^{Observed}$ is the observed velocity at time i, and $v_i^{Predicted}(\theta_i)$ is the velocity based on the model output using the parameter set θ_i

- Step 2: Fine-tuning using an RL setup:
  - State: Acceleration, speed, heading, and parameter offset.
  - Action: Small, simultaneous nudge to each tunable dimension.
  - Reward: Expert rating of model performance.



Research Results

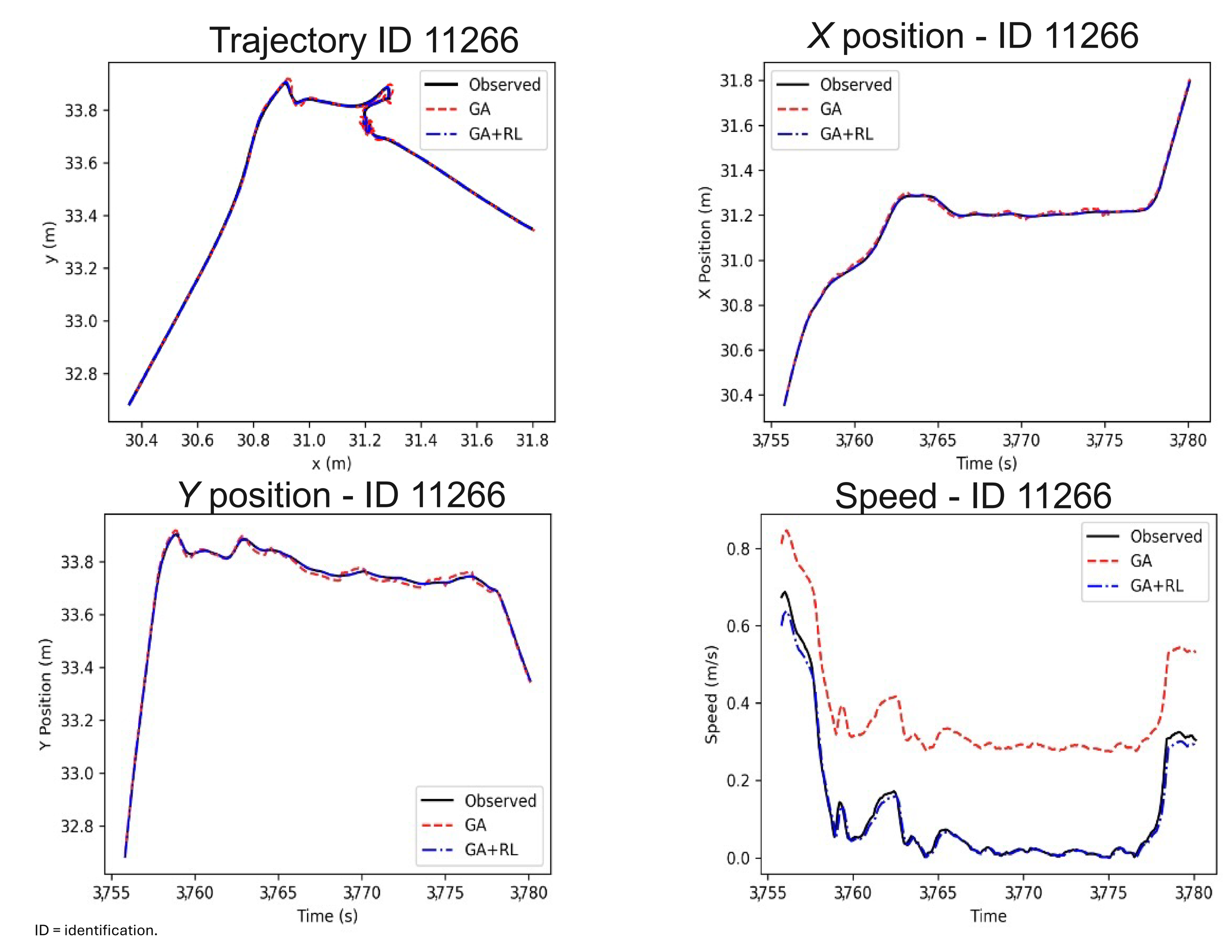


Figure 1. Predicted versus observed position and speeds along two axes for a sample agent using the SF.

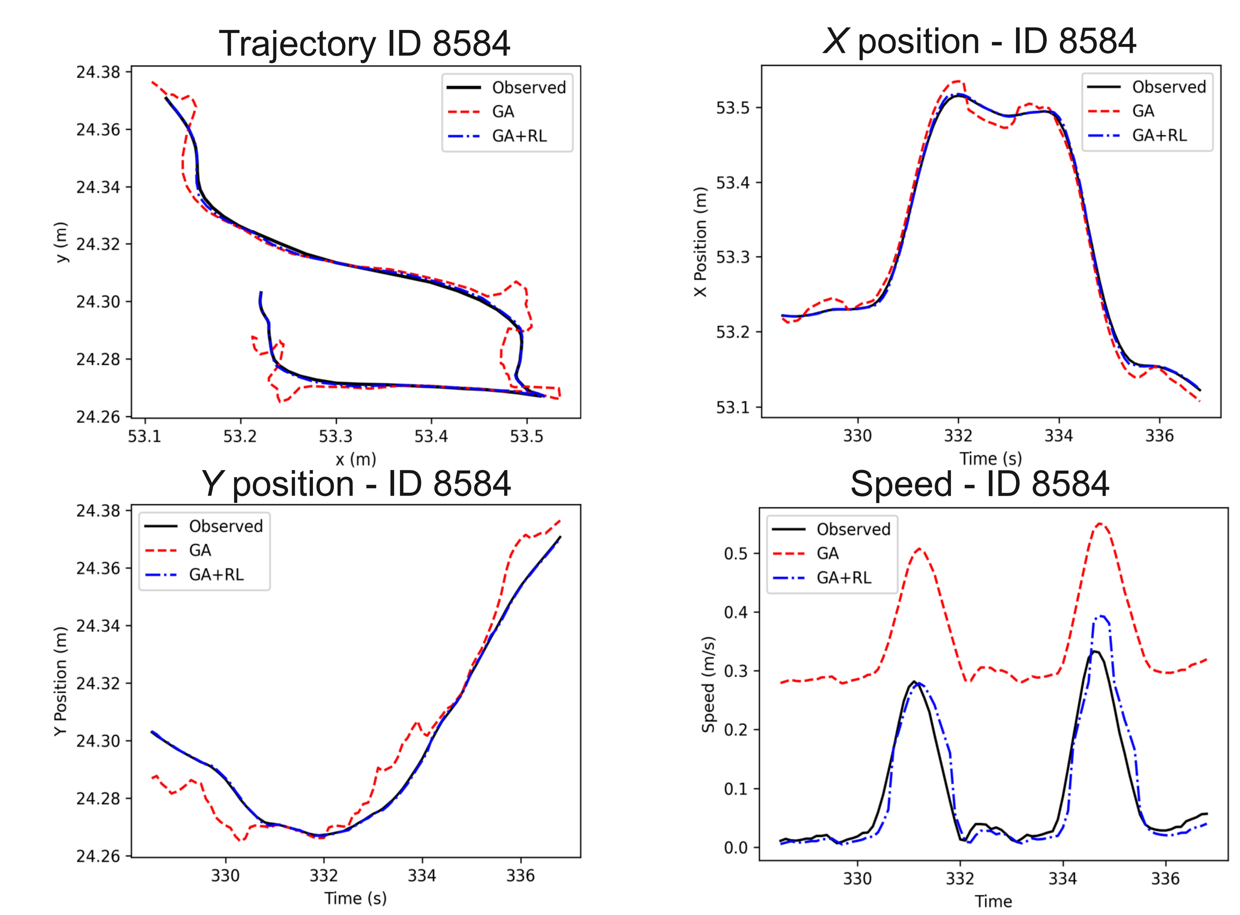


Figure 2. Predicted versus observed position and speeds along two axes for a sample agent using the PT.

Conclusions

- Calibration significantly improved different error metrics across both models and modes.
- SFM generally outperformed PT for pedestrians, whereas PT performed better for bicycles in noisy environments.
- Noisy input analysis showed robust model performance, although accuracy dropped compared to clean data, especially in PT bicycle simulations.
- Correlation analysis confirmed stronger parameter stability for SFM across varying noise levels.

All images are source: FHWA.

References

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