A Visual Driving Rule-Based (VDR) Car-Following Model based on Dynamic Visual Features

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Abstract

Conventional car-following models describe driver response using physical variables such as spacing, relative speed, and ego speed, although drivers regulate their motion through imperfect visual perception. This study develops a Visual Driving Rule (VDR) car-following model based on the preceding vehicle's perceived visual width, its expansion rate, optical flow rate, and vehicle class. The model parameters vary across visual perception and across drivers. Camera projection provides interpretable relationships between the visual variables and physical traffic states. The analysis explicitly represents persistent bias and noise in perceived visual width, expansion rate, and optical flow, and examines how these errors interact with model parameters to affect traffic flow stability. Approximately 170 minutes of naturalistic dashcam data from four drivers are used to characterize visual features and to estimate optical flow directly from driving video. 30,000 car-following events detected by roadside LiDAR (Light Detection and Ranging) provide high-quality physical trajectories for camera projection calibration and model parameter estimation. The results show that the proposed model reproduces trajectories for both passenger-car and heavy-vehicle leaders and yields lower speed errors than the reference models. The stability analysis is conducted to explore the impact of visual perceptions on traffic flow stability. This framework connects empirical visual perception, heterogeneous driver response, and traffic stability within one interpretable car-following model.

Keywords: Car-Following Model, Camera Projection

Introduction

Problem Statement

- Car-following models play a foundational role in traffic flow theory. Most car-following models typically rely on three key inputs: the spacing headway, the relative speed, and the ego vehicle's own speed.
- However, human drivers do not perceive spacing and relative speed directly through precise physical measurements.

Research Motivations

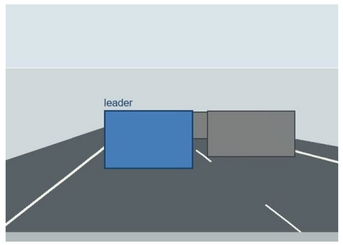
- Advances in Computer Vision technologies and data collection technologies.
- Emerging trend in vision-based self-driving and 3D traffic simulation.

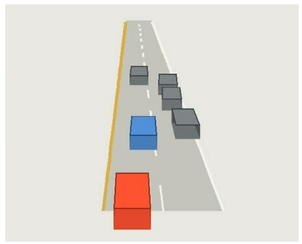
Research Goal

- Develop a human-like car-following model driven by comprehensive visual information, reflecting how human drivers perceive and react to surrounding traffic.
- Seeks to bridge the gap between human perceptual models and machine-driven car-following systems.
- Contribute both to microscopic traffic flow theory and to the development of more human-like, vision-based ADAS technologies and traffic simulations.

Research Contributions

- Advance understanding of vision-based driver perception and its role in car-following behavior.
- Support the development of vision-based collision avoidance algorithms for intelligent vehicles.
- Enable next-generation 3D traffic and sensor simulation through visual information modeling.
- Introduce a novel, low-cost data collection method using dashcams or mobile devices





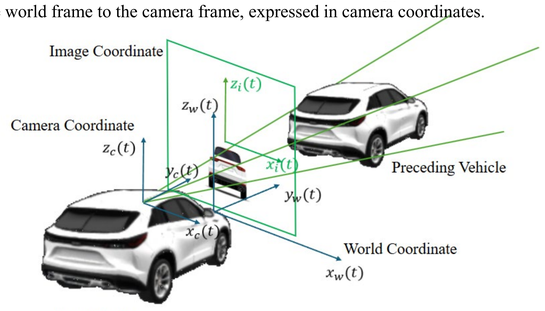
Methodology

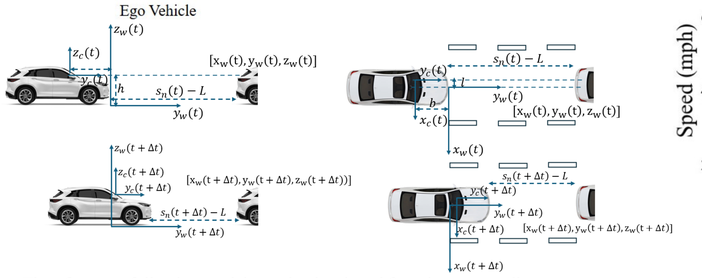
Coordinate Transformation (World Coordinates -> Image Coordinates)

- Every point from 3D world coordinate system has a corresponding point in 2D image coordinate system
- The relationship can be established using the matrix transformation

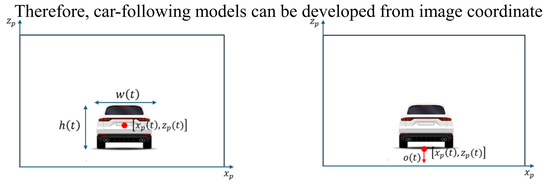
$$X_c = R_{cw}X_w + t_{cw}$$

where X_c is coordinates of a point in the camera coordinate system. X_w is coordinates of the same point in the world coordinate system. R_{cw} is rotation matrix transforming coordinates from the world frame to the camera frame. t_{cw} is translation vector from the world frame to the camera frame, expressed in camera coordinates.





Therefore, car-following models can be developed from image coordinate



Traditional Car-Following Formula	Visual Car-Following Formula
$a_n(t+\tau) = f(s(t), \Delta v(t), v(t))$	$a_n(t+\tau) = f(w(t), \dot{w}(t), o(t))$
$a_n(t+\tau)$: acceleration/deceleration of driver n at time $t+\tau$	$a_n(t+\tau)$: acceleration/deceleration of driver n at time $t+\tau$
τ: reaction time	τ: reaction time
$s(t)$: spacing headway at time t	$w(t)$: perceived visual width at time t
$\Delta v(t)$: relative speed at time t	$\dot{w}(t)$: perceived visual expansion rate at time t
$v(t)$: ego speed at time t	$o(t)$: perceived optical flow rate at time t

Proposed Visual Driving Rule (VDR) car-following model

$$a_n(t+\tau) = K_p\left[\frac{1}{w(t)} - \frac{o(t)}{K}\right] - K_d\frac{\dot{w}(t)}{w^2(t)}$$

K_p: proportional gains applied to the visual width of the leading vehicle

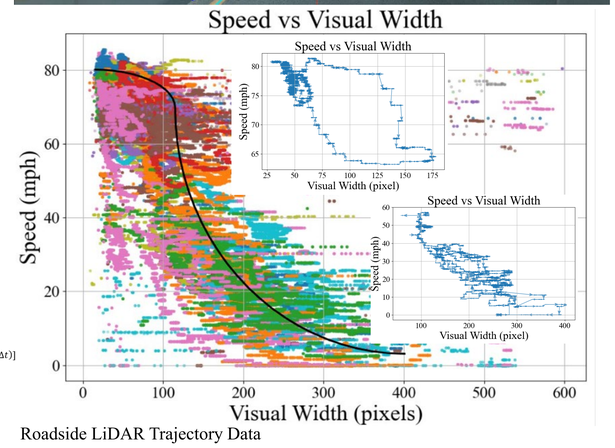
K_d: derivative gains applied to the visual expansion rate of leading vehicle

K: driver's following aggressiveness in perceptual space, determining the desired visual width for a given optical flow rate. Larger K corresponds to more aggressive driving with smaller following spacing, while smaller K corresponds to more conservative driving with larger following spacing.

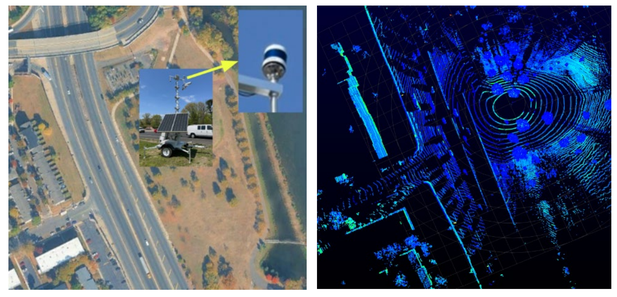
Real-World Data

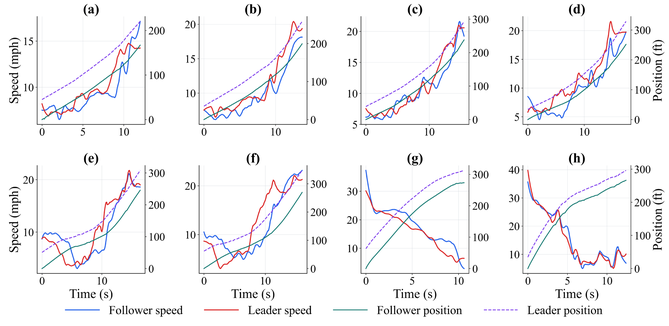
Naturalistic Driving Data (Dashcam + Mobile Sensor)





Roadside LiDAR Trajectory Data





Model Performance

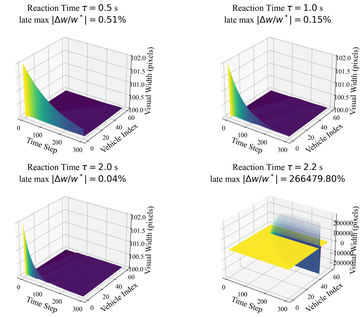
The proposed VDR model was compared with the Intelligent Driver Model (IDM) and the Optimal Velocity Model (OVM)
The proposed VDR model produced the lowest speed RMSE for both following-car and following-heavy-vehicle events

Leader Class	VDR	IDM	OVM
	Speed RMSE (mph)		
Car	2.409	2.960	4.668
Heavy Vehicle	2.092	3.309	4.444

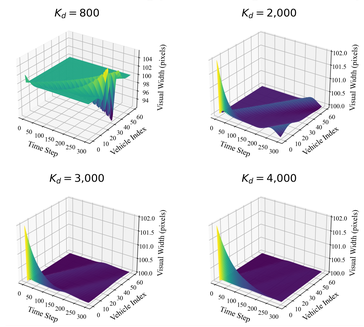
Stability Analysis

We perform stability analysis to evaluate how small perturbations from equilibrium propagate through a platoon and determine whether small perturbations decay or amplify over time

- For example, if the reaction time is large, it tends to lead to more unstable conditions. This aligns with the theory that large delays in driver response can destabilize traffic flow



- If the derivative gain K_d is large, it tends to lead to more stable conditions. As K_d increases, the vehicle becomes more responsive to changes in the visual width expansion rate, reducing perturbation growth and improving traffic stability



Conclusion and Future Work

- Proposed a visual car-following model that models driver perception-reaction using visual cues instead of physical measurements.
- Calibrated the model using naturalistic driving data and LiDAR trajectories.
- Evaluated the model by comparing it to well-known traditional models.
- Conducted stability analysis and numerical simulations to validate the model's ability to reproduce realistic traffic phenomena.
- Future work: expand this model to include more visual inputs, including braking light, neighboring lane traffic, depth perception, etc. Expand the stability analysis to include a nonlinear relationship between visual perception and following distance.