Condensed Representation Learning for Interactive Driving Styles Recognition

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Abstract

Automated vehicle (AV) validation faces the "billions of miles" challenge, requiring high-fidelity simulations to replicate diverse interactive driving behaviors for safety. Traditional methods oversimplify by using uniform behavioral models, ignoring the diversity of human driving styles, which are deeply influenced by individual psychological traits. This research introduces a condensed framework for representing interactive driving styles, by incorporating these psychological dimensions, balancing completeness and complexity. Key features include: i) individual style recognition via attention mechanisms and hierarchical contrastive learning, capturing subtle cognitive-based interaction patterns that reflect underlying differences in driver psychology (e.g., risk tolerance, decision-making heuristics); ii) scenario-independent style compression, filtering external factors to extract intrinsic driver intentions; iii) dimensionality-aware refinement, mapping complex behaviors to low-dimensional psychological axes for efficient computation. Tests on the NGSIM dataset reduced testing complexity by decoupling styles from scenarios. Compared to traditional methods, style distinctiveness improves by 28% (entropy-based), with 85% edge-case behavior coverage. This framework supports scalable AV testing by integrating diverse, psychologically-informed driving styles without combinatorial complexity.

Keywords: automated vehicle testing; interactive driving styles recognition; scenario-consistent style compression; psychological behavioral modeling; testing completeness-complexity trade-off

Introduction

Automated vehicle (AV) testing requires massive data to ensure safety—a challenge known as the "billions of miles" problem, which physical testing cannot meet alone (Feng et al., 2023). High-fidelity simulations offer a scalable solution by replicating complex driving scenarios (Wang, Hu, & Lai, 2023), such as those involving specific applications like truck platooning in interactive environments (Hu et al., 2024). To further accelerate the evaluation process, (Wu, Xing, Xiong, & Chen, 2024) proposed a dual-surrogate-based framework that enhances testing efficiency while maintaining realism, highlighting the importance of surrogate models in scalable validation pipelines. However, modeling realistic vehicle interactions—particularly those influenced by individual psychological traits—remains a critical challenge. Traditional models often overlook psychological traits like risk tolerance and decision-making heuristics, which influence behavior in both routine and edge cases. Capturing these traits is key to comprehensive AV validation.

While high-fidelity simulations address the "billions of miles" challenge by recreating realistic scenarios, conventional methods often oversimplify interactions with uniform behavioral models. These models homogenize driver parameters (e.g., fixed reaction time (Huo, Ma, & Chang, 2020; Y. Zhang, Ma, Qu, & Zhou, 2024)) or apply identical decision rules to all agents (C. Zhang et al., 2024; Z. Zhang, Lai, Ma, Zhu, & Yang, 2021; Z. Zhang, Lai, & Yang, 2022), ignoring the psychological diversity in human driving styles

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(e.g., shifts in cognitive load or emotion regulation). In reality, AVs must adapt to both environmental conditions(e.g., complex highway scenarios as explored by Wang et al., 2025) and diverse agent behaviors. This demands psychologically grounded, multi-style modeling to accurately reproduce interactions. Missing these variations risks excluding critical edge cases and undermining testing completeness(Duan et al., 2024). Incorporating psychological differences, like trait-based vs. situational risk-taking, is key to closing this gap.

The heterogeneity of interactive behaviors arises from variations in individual driving styles. Achieving diverse simulations requires systematic identification and modeling of these stylistic differences. Current recognition methods follow two main paradigms: discrete clustering and continuous indexing (Martinez, Heucke, Wang, Gao, & Cao, 2017). Discrete clustering assigns agents to fixed categories (e.g., "aggressive" or "conservative") (Brombacher, Masino, Frey, & Gauterin, 2017; J. Peng, Tang, Wang, Gu, & Peng, 2024; H. Zhang & Fu, 2021), but ignores variations within clusters. Continuous indexing uses operational metrics (e.g., acceleration, time-to-collision) to quantify styles (De Rango, Tropea, Serianni, & Cordeschi, 2022; Mohammadnazar, Arvin, & Khattak, 2021; Y. Peng, Cheng, Jiang, & Zhu, 2021), yet reduces complex behaviors to scalar values, overlooking psychological factors like anxiety or overconfidence. Hybrid methods embed style recognition in prediction or control networks via latent features (Mo, Xing, & Lv, 2020; Xing et al., 2019), but their objectives (e.g., trajectory accuracy) (Deo & Trivedi, 2018; Geng, Chen, Xia, & Chen, 2023) often misalign with style recognition, leading to unvalidated and biased results. This highlights the need for psychological models that explicitly represent individual interactive styles while preserving behavioral detail.

While the integration of diverse driving styles enhances testing completeness, their combinatorial explosion with complex scenarios creates a critical scalability barrier. This combinatorial challenge arises from two compounding factors: (1) the exponential growth of scenario-style permutations, and (2) the high-dimensional representation of styles that often encode redundant or scenario-specific features. To reconcile this tension between completeness and complexity, there are two synergistic strategies: decoupling style representation from scenario constraints and compressing style dimensions through feature refinement:

Non-scenario-dependent style characterization. Existing methods often tie style identification to specific scenarios, leading to rigid, non-generalizable models (Augustynowicz, 2009). This limits style transferability and increases complexity, requiring retraining for each new scenario. In contrast, scenario-independent recognition focuses on intrinsic traits consistent across contexts. Decoupling styles from scenarios allows for reusable models that adapt dynamically, reducing redundancy and improving testing efficiency.

Dimensionality-aware style compression. Current high-dimensional style representations strain computation and reduce interpretability. Refining them into low-dimensional, meaningful features serves two goals: (1) removing redundant parameters with minimal behavioral impact, and (2) enabling efficient style recombination across scenarios. This compression balances completeness and complexity, allowing AVs to encounter diverse behaviors without overloading simulations.

In the paper, a method for recognizing interactive driving styles is proposed.

Methodology

Model structure

To achieve a condensed representation of interactive driving styles, the proposed model is structured into three core modules: Trajectory Data Preprocessing, Interaction Intention Extraction, and Interactive Style Condensation (Fig. 1).

The first module segments trajectory data and encodes it with ego-vehicle and scenario context. The second infers interaction intentions using ego and surrounding vehicle behaviors. The third filters out scenario-specific factors, producing a compact, scenario-independent representation of interactive driving styles.

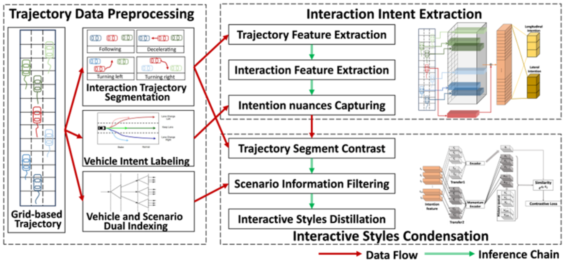

Figure 1: Model structure

Trajectory Data Preprocessing

The preprocessing module segments ego-vehicle trajectories based on operational states, identifying four types of interaction: following, decelerating, and turning left and turning right. It extracts motion-based longitudinal and lateral intentions and encodes the resulting segments with scenario and vehicle ID information for model training.

Interaction Intention Extraction

This module identifies ego-vehicle driving intentions by filtering out environmental noise and consists of four sub-modules.

It first extracts trajectory features using an LSTM network to model temporal patterns and enhance stability. Then, a Transformer-based attention mechanism captures multi-agent interactions.

The combined features are processed by a multi-task classifier to reconstruct longitudinal and lateral intentions, enabling fine-grained recognition of interaction patterns.

Interactive Style Condensation

Module Structure

To ensure scenario-agnostic style recognition, this module employs contrastive learning to filter environmental influences from interaction intentions. It further condenses interactive styles through encoder fine-tuning.

Contrastive Trajectory Segment Learning

Interaction intentions are dual-encoded, with samples from the same vehicle treated as positives. The encoder learns to group these together, generating distinctive style embeddings.

Scenario Information Filtering

A scenario filter further removes context-dependent features, ensuring the resulting representations reflect consistent driving styles across different environments.

Model Training and Implementation

The model adopts a hierarchical training framework comprising two sequential phases. In Phase 1, the interaction intent extraction network is trained to reconstruct longitudinal and lateral interaction intentions, with its effectiveness validated through intention prediction accuracy. The loss function for this phase combines cross-entropy losses for longitudinal and lateral intention reconstruction, formulated as:

$$L_{long} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{3} y_{i,c} \log\left(\frac{e^{\hat{y}_{i,c}}}{\sum_{j=1}^{3} e^{\hat{y}_{i,j}}}\right) \tag{1}$$

$$L_{lat} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{3} y_{i,c} \log\left(\frac{e^{\hat{y}_{i,c}}}{\sum_{j=1}^{3} e^{\hat{y}_{i,j}}}\right) \tag{2}$$

$$L_1 = \alpha L_{long} + (1-\alpha) L_{lat} \tag{3}$$

Where L_{long} and L_{lat} denote cross-entropy losses for longitudinal and lateral intention classification; denote the total number of samples, $y_{i,c}$ represent the ground-truth intention labels, and $\hat{y}_{i,c}$ correspond to the predicted intention labels.

In Phase 2, the pre-trained parameters are transferred to the interactive style condensation module, which receives dual-encoded trajectory fragments (vehicle signature and scenario context) as supplementary inputs. This module employs contrastive learning to minimize intra-driver style variance while maximizing inter-driver distinctions.

Result

Dataset

The model is trained and evaluated on the NGSIM I-80 dataset (Colyar & Halkias, 2006), which provides high-resolution vehicle trajectories at 10 Hz, including position, speed, and lane changes.

A 3×13 spatial grid captures local interaction dynamics across a 180-foot longitudinal and 36-foot lateral range.

Compared model

To enable fair comparison, we adopted Augustynowicz (2009)'s continuous driving style identification framework, which processes three steps: (1) selecting vehicle operational metrics, (2) scaling them to [0,1] via linear normalization, and (3) calculating normalized metric averages as unified scores (0.9=maximally aggressive, 0.1=extremely mild, with linear interpolation between). This multidimensional aggregation offers objective classification and establishes a dynamic scenario evaluation baseline.

Individual-level styles recognize

Our method recognizes individual driving styles by capturing each vehicle's unique interaction patterns and clearly distinguishing between different vehicles' behaviors, improving test coverage.

Style Distinctiveness

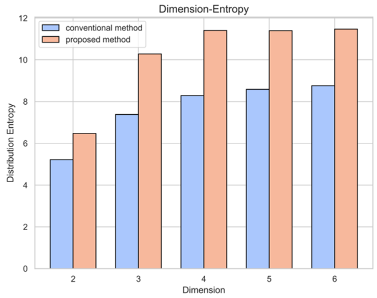

Figure 2: Style Distribution Entropy Across Different Dimensions of Interactive Driving Styles

Style distinctiveness is evaluated via Style Distribution Entropy, where higher values reflect greater behavioral diversity between vehicles. The entropy is defined as:

$$E = -\sum_{i=1}^{B} p_i \cdot \log p_i \tag{4}$$

where B is the number of sampling iterations, and p_i denotes the number of samples included in each iteration.

As shown in Fig. 2, our method achieves higher entropy across all dimensions than the baseline, indicating it better distinguishes between individual interactive driving styles.

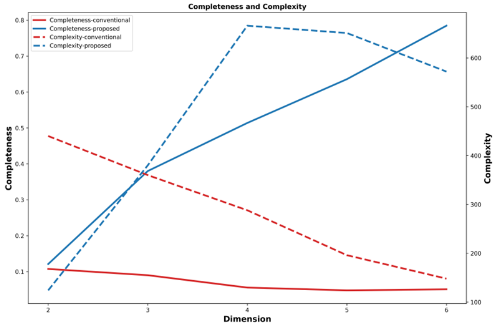

Figure 3: Completeness and Complexity of Testing across Different Dimensions of Interactive Styles

Balance between testing completeness and complexity

The method balances testing completeness and complexity by adjusting the dimensionality of interactive driving styles.

Completeness and complexity are quantified by sampling coverage (ratio of samples to population) and sampling frequency (number of iterations). Traditional scenario-sensitive methods require more iterations as scenario count increases.

As shown in Fig. 3, our method achieves broader coverage with fewer iterations by filtering scenario-specific factors, supporting efficient yet comprehensive testing through dimensionality tuning.

Conclusion

This study presents a condensed representation framework for interactive driving styles, grounded in the understanding that these styles are manifestations of drivers' underlying psychological characteristics (such as risk perception and decision-making tendencies), addressing the trade-off between testing completeness and complexity in AV validation.Key contributions include:

Individual-level style recognition: Leveraging attention and hierarchical contrastive learning, the method achieves >90% recognition confidence, effectively distinguishing intra-driver nuances and inter-driver differences. Driving styles are modeled as expressions of psychological traits; this psychological grounding is crucial for capturing the authentic diversity of human behavior.

Balanced testing efficiency: Dimensionality-aware refinement enables trade-offs, achieving 28% higher style distribution entropy and maintaining 85% edge-case coverage with lower computational cost.

Experimental results confirm the method’s scalability and ability to capture heterogeneous behaviors. Future work will extend to multi-agent reinforcement learning, real-time style adaptation, and interpretable cognitive-behavioral representations that aim to elucidate the psychological drivers and cognitive processes behind observed driving actions, thereby fostering greater trust in safety-critical applications.

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