

Interaction Behavior Characteristics between Autonomous Vehicles and Pedestrians: A Lag Sequential Analysis Approach

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Abstract: In urban mixed traffic scenarios, interactions between autonomous vehicles and pedestrians exhibit high randomness and strategic diversity, making it challenging to derive interpretable sequential evidence of behavioral characteristics through instantaneous metrics. This paper proposes a micro-level interaction behavior feature extraction method based on Lag Sequential Analysis (LSA). This study constructs vehicle–pedestrian interaction samples based on the nuScenes autonomous driving dataset, extracting valid interaction segments under constraints of an interaction distance threshold of 30 m and conflict screening criteria. Continuous motion trajectories of vehicles and pedestrians are discretized into behavioral state codes, forming single-channel interaction event sequences. Adjusted Residuals (ADJR) are computed under first-order lag conditions to test the statistical significance of state transitions, identifying stable, significant transition paths and behavioral chain structures. Results demonstrate significant sequence dependencies between stable vehicle driving and pedestrian decisions such as “approach/pause.” Interaction processes can be categorized into behavioral characteristics including intent uncertainty, risk aversion, efficiency orientation, and dynamic right-of-way negotiation, revealing stable, significant transition chains such as “vehicle confirmation—accelerated passage” and “pedestrian wait—vehicle passage.” The identified significant behavioral chains provide interpretable, testable quantitative evidence supporting the expression of interactive intent, pedestrian behavior prediction, and autonomous driving planning decisions.

1. Introduction

As autonomous vehicles enter open-road environments, the negotiation process between vehicles and pedestrians undergoes a fundamental transformation. Traditional interactions that rely on social cues such as driver eye contact or hand gestures are progressively replaced by a decision-making process jointly driven by vehicle motion states, pedestrian risk perception, and road regulations ^[1-2].

Existing research has explored vehicle–pedestrian interaction mechanisms from multiple

perspectives. At the behavioral level, road users primarily infer intentions through implicit motion cues—such as deceleration, distance adjustment, and lateral positioning—rather than explicit communication like waving or nodding^[3-4]. Notably, pedestrian crossing strategies including hesitation, waiting, and darting behaviors are consistently observed in both controlled experiments and field studies. Mutual gaze (eye contact) and the dynamic evolution of vehicle kinematics jointly shape pedestrians' risk judgments, forming a bidirectional adaptation process during interaction^[5]. Lack of right-of-way rules at unmarked mid-block crossings hinders pedestrian-vehicle coordination, requiring stricter AV decision-making^[6].

Regarding interaction modeling, researchers have developed high-level behavioral models, rule-based frameworks, and learning-based approaches to describe pedestrian responses and negotiation behaviors. Complementarily, traffic conflict techniques and surrogate safety measures (e.g., time-to-collision, post-encroachment time) quantify interaction risks by observing potential conflict behaviors^[7-9].

However, existing studies mainly rely on instantaneous indicators or high-level behavioral descriptions, which makes it difficult to reveal statistically significant temporal dependencies in vehicle–pedestrian interaction processes. To address these limitations, this paper introduces Lag Sequential Analysis (LSA) to model vehicle–pedestrian interactions as an observable discrete state transition process^[10]. Based on the nuScenes dataset^[11], which comprises 1,000 carefully selected 20-second driving scenarios from Boston and Singapore featuring diverse traffic operations and challenging conditions, we extracted continuous trajectories of vehicles and pedestrians. Using official 3D annotations and the DevKit, key state parameters—including coordinates, velocities, vehicle–pedestrian distances, and point cloud counts—were obtained. A behavior coding system was then constructed based on relative spatial–temporal relationships and motion dynamics, discretizing continuous interactions into enumerable state sequences. Using GSEQ^[12], we statistically validated state transitions and extracted stable behavioral chains, transforming qualitative interactions into quantifiable sequences for cross-scenario pattern analysis.

This paper introduces a unified interaction analysis framework that defines reproducible segment boundaries via traffic conflict techniques, extracts key behavioral chains through urban-specific coding and Lag Sequential Analysis, and validates the approach on nuScenes data to support downstream intention prediction and planning.

2. Data Sources and Preprocessing

Unlike traditional human-driven environments, conflict definitions for autonomous vehicles must account for perception uncertainty and safety models. This paper defines traffic conflicts between autonomous vehicles and pedestrians as: a dynamic process occurring under quantifiable spatiotemporal conditions where both parties' trajectories approach a critical threshold, and failure to implement proactive avoidance strategies would cause the minimum safe distance to breach the safety margin boundary.

This study utilizes the nuScenes dataset as its experimental foundation, leveraging its multi-sensor 3D annotations across diverse urban environments to extract key vehicle and pedestrian state parameters—including coordinates, velocity, inter-agent distance, and point cloud counts—via the official DevKit.

To construct high-quality data suitable for interaction analysis, this study preprocessed the dataset by associating historical trajectories using keyframe annotations and instance identifiers. It employed positional differential methods and backward interpolation to calculate the velocity of autonomous vehicles and pedestrians at each time step. Samples exhibiting extreme height anomalies or excessive distance were excluded to eliminate sensor noise and interference from atypical obstacles. All

pedestrian absolute coordinates were transformed into a local coordinate system relative to the autonomous vehicle to facilitate unified analysis of relative distance and approach velocity. During specific filtering, considering the long-range perception capability of autonomous sensors, 30 meters was typically set as the boundary for the perception range. Therefore, straight-line distance was adopted as a direct metric for interaction intensity, with an interaction distance threshold of 30 meters. When the distance between the vehicle and a pedestrian is less than 30 meters, it is considered to have entered the potential interaction range; when the distance exceeds 30 meters, the interaction ends. Ultimately, this study constructed a sequential dataset containing 8,688 independent vehicle-pedestrian interaction segments, covering 121,125 discrete time steps, providing reliable data support for subsequent analysis.

3. Behavior Encoding and Analysis Methodology

Employing Sackett’s LSA^[10], we discretize AV–pedestrian interactions into states and use first-order lag (lag=1) with adjusted residuals to validate non-random transitions, yielding assumption-free behavioral chains as the statistical foundation for pattern extraction.

3.1 Definition and Coding of Interaction Behavior States

Lag sequence analysis requires discretizing continuous trajectory measurements into enumerable “behavior/state codes.” This study employs threshold-based operational definitions to encode vehicles and pedestrians as finite state sets, generating state sequences within the interaction range. Vehicle speed, acceleration, and yaw rate are utilized for subsequent state classification.

(1) Vehicle Kinematic Quantity Calculation

Vehicle velocity and acceleration are derived from positional differences between adjacent time points, where equation (1) calculates instantaneous velocity and equation (2) computes acceleration based on velocity differences.

$$v(t) = \frac{\|p(t) - p(t - \Delta t)\|}{\Delta t} \quad (1)$$

$$a(t) = \frac{v(t) - v(t - \Delta t)}{\Delta t} \quad (2)$$

Where $p(t) = [x(t), y(t), z(t)]^\top$ denotes the vehicle’s global position and Δt represents the sampling period. Experimental data employs a 2Hz sampling rate, corresponding to $\Delta t = 0.5s$.

Equation (3) calculates the vehicle’s heading angular velocity by differentiating the heading angle over consecutive time steps, providing a quantitative measure of steering behavior derived from quaternion-based attitude transformation.

$$\dot{\psi}(t) = \frac{\psi(t) - \psi(t - \Delta t)}{\Delta t} \quad (3)$$

(2) Pedestrian Velocity and Relative Distance Change Rate

Equation (4) synthesizes the pedestrian’s scalar velocity magnitude from orthogonal velocity components, enabling a simplified representation of pedestrian movement intensity for behavioral state coding.

$$v_p(t) = \sqrt{v_{px}^2(t) + v_{py}^2(t)} \quad (4)$$

Equation (5) defines the relative distance change rate between vehicle and pedestrian, where

negative values indicate approach behavior and positive values represent retreat behavior in their interaction dynamics.

$$\dot{d}(t) = \frac{d(t) - d(t - \Delta t)}{\Delta t} \quad (5)$$

When the sampling frequency is 2Hz, $\dot{d}(t) \approx 2 \cdot (d(t) - d(t - 1))$. Here, $\dot{d}(t) < 0$ denotes a decrease in distance between pedestrian and vehicle (approach), $\dot{d}(t) > 0$ denotes an increase in distance (retreat).

(3) Autonomous Vehicle Behavior Encoding

Equation (6) formally defines the vehicle state set comprising five discrete behavioral codes (VS, VA, VD, VT, VK) that categorize autonomous vehicle motion patterns for sequential analysis.

$$\mathcal{S}_v = \{VS, VA, VD, VT, VK\} \quad (6)$$

Autonomous vehicles are coded according to five behavioral states, as shown in Table 1.

Table 1: Vehicle Behavior State Coding Table.

Code	Behavior	Explanation
VS	Stationary/Near-stationary	Vehicle at standstill or moving at low speed (yielding to traffic, queuing, etc.)
VA	Acceleration	Vehicle accelerating (increased intent to proceed/initial stages of departure)
VD	Deceleration	Vehicle slowing down (preparing to observe or yield, reducing collision risk)
VT	Turning	Vehicle changing direction (e.g. left turn, right turn)
VK	Maintaining Steady State	Vehicle speed/posture showing no significant change, maintaining forward motion

(4) Pedestrian Behavior Coding

Equation (7) specifies the pedestrian state set containing four behavioral codes (PS, PA, PT, PK) that represent distinct pedestrian movement patterns during vehicle interactions.

$$\mathcal{S}_p = \{PS, PA, PT, PK\} \quad (7)$$

Pedestrians are coded into four behavioral states, as shown in Table 2.

Table 2: Pedestrian Behavior State Coding Table.

Code	Behavior	Explanation
PS	Pausing/Waiting	Pedestrians halt (observing, waiting/decision-making pause)
PA	Approaching	Distance between pedestrians and vehicles decreases
PT	Moving Away/Passing	Distance between pedestrians and vehicles increases; depart after completing crossing
PK	Maintaining Steady State	State where distance between pedestrian and vehicle shows no significant change

3.2 Construction and Vectorization of Interaction Event Sequences

This study focuses on the ‘behavioral switching mechanism’ rather than state duration. Therefore, repeated adjacent states for the same subject are compressed to reduce redundancy and emphasize state transitions. Specifically, only the first occurrence of a consecutively repeated identical state is

retained, thereby emphasizing the ‘state transition’ itself.

(1) Fundamental Units of Interaction Sequences

Equation (8) represents the fundamental unit of interaction sequences, capturing paired vehicle-pedestrian state codes at each time step within the defined 30-meter interaction threshold boundary.

$$s_v(t) \in \mathcal{S}_v, \quad s_p(t) \in \mathcal{S}_p \quad (8)$$

This process generates an encoded data table containing the following fields: interaction sequence identifier, time index, $s_v(t)$, $s_p(t)$.

(2) Construction of Interaction Event Sequences

Although several tools are available for behavioral data analysis, their complex operations often require specialized expertise. To provide convenient and efficient behavioral data processing support, Bakeman and Quera collaboratively developed GSEQ (General Sequential Querier), specialized software for interaction behavior analysis. This tool not only streamlines behavioral analysis workflows and enhances data processing efficiency but also promotes the widespread application of LSA across various fields. To accommodate GSEQ’s event-type input, the ‘vehicle-pedestrian’ interactions were converted into single-channel event sequences, laying the groundwork for subsequent time-lag analysis. Equation (9) demonstrates the construction of single-channel event sequences by alternately concatenating vehicle and pedestrian state codes, creating the required input format for Lag Sequential Analysis in GSEQ software.

$$S = [s_v(t_1), s_p(t_1), s_v(t_2), s_p(t_2), \dots, s_v(t_n), s_p(t_n)] \quad (9)$$

Among these, t_1, \dots, t_n represents the time series for this interaction sequence.

(3) Organization of GSEQ Input Files

GSEQ input comprises two components: 1) Event Codes list (declaration of event code sets); 2) Event sequences output by interaction sequence.

3.3 LSA-Based Model for Identifying Significant Behavioral Chains

(1) First-Order Lag Transformation Statistics

Let the overall event set for interactions be $\mathcal{C} = \mathcal{S}_v \cup \mathcal{S}_p$. Equation (10) constructs the transition frequency matrix for first-order lag analysis, recording how frequently each behavioral state transitions to another state within the interaction sequences.

$$O_{ij} = \#\{k \mid S_k = i, S_{k+1} = j\}, \quad i, j \in \mathcal{C} \quad (10)$$

Where S_k denotes the event code at the k position in the sequence.

Equation (11) calculates the row and column sums of the transition frequency matrix, which serve as essential components for determining expected transition frequencies under the null hypothesis of behavioral independence.

$$R_i = \sum_j O_{ij}, \quad C_j = \sum_i O_{ij}, \quad N = \sum_i \sum_j O_{ij} \quad (11)$$

Equation (12) computes the expected frequency of state transitions assuming behavioral independence, establishing the baseline against which actual transition frequencies are compared for significance testing.

$$E_{ij} = \frac{R_i C_j}{N} \quad (12)$$

(2) Adjusted Residuals and Significance Testing

To test whether a given transition is significantly higher (or lower) than the independence expectation, this study employs the adjusted residual (ADJR) output by GSEQ as the significance indicator. Equation (13) defines the adjusted residual (Z-score) statistic used to evaluate whether observed behavioral transitions significantly deviate from random expectations, if $Z_{ij} > 1.96$, the transition is deemed significant at the $\alpha = 0.05$ significance level. with $Z > 3.29$ indicating statistical significance at $p < 0.001$. Hereafter, this is uniformly referred to as ADJR(Z).

$$Z_{ij} = \frac{O_{ij} - E_{ij}}{\sqrt{E_{ij} \left(1 - \frac{R_i}{N}\right) \left(1 - \frac{C_j}{N}\right)}} \tag{13}$$

where Z_{ij} approximately follows a standard normal distribution under a sufficiently large sample size.

4. Results and Discussion

4.1 Statistical Significance of Interaction Behavior Transfers

GSEQ outputs first-order lag adjusted residuals (ADJR) as z-statistics to assess transition significance: positive values indicate transitions occurring more frequently than expected by chance, whereas negative values indicate transitions occurring less frequently than expected by chance. Per LSA theory, $Z > 3.29$ ($p < 0.001$) denotes statistically significant behavioral pathways, as summarized in Table 3.

Table 3: Adjusted Residuals (ADJR) Matrix for First-Order State Transitions.

From/To	PA	PT	PK	PS	VA	VD	VK	VS	VT
PA	0	-93.73	-38.64	-121.3	55.46	58.11	72.15	58.85	31.51
PT	-94.44	0	-26.53	-83.29	44.8	45.37	46.78	89.88	26.39
PK	-39.75	-27.09	0	-35.06	25.95	20.98	29.17	41.6	9.01
PS	-121.51	-82.8	-34.14	0	63.52	54.92	74.75	44.37	48.54
VA	54.62	46.66	20.12	56.99	0	-42.24	-72.85	-59.03	-25.25
VD	56.12	43.71	20.75	50.7	-42.22	0	-68.32	-55.36	-23.68
VK	69.8	46.1	27.05	71.56	-73.46	-68.92	0	-96.31	-41.2
VS	53.34	79.89	40.73	45.5	-58.26	-54.66	-94.28	0	-32.67
VT	30.22	23.49	8.48	47.32	-25.25	-23.69	-40.86	-33.1	0

Based on the adjusted residual data table generated by GSEQ, a behavioral transition diagram for autonomous vehicles and pedestrians was plotted, as shown in Figure 1.

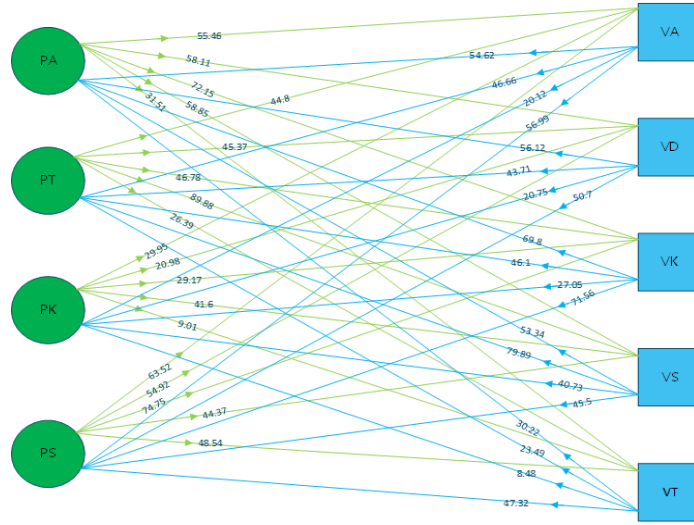


Figure 1: Behavioral transition diagram for autonomous vehicles and pedestrians.

4.2 Analysis of Vehicle-Pedestrian Interaction Behavior Characteristics

Based on the adjusted residual table and behavioral transition diagram derived from lagged sequence analysis, this study quantitatively summarizes the interaction characteristics between autonomous vehicles and pedestrians in urban road environments. The significance levels of these characteristics have all passed statistical testing, revealing the underlying mechanisms within the interaction process.

Characteristic 1: Intent Uncertainty.

Stable AV motion may create ambiguous yielding cues for pedestrians, leading to either approaching or waiting behavior. The Z-values for pedestrian approach (VK→PA, Z=69.80) and pedestrian stop (VK→PS, Z=71.56) are both significant and numerically close, indicating that stable AV motion may lead pedestrians to either attempt crossing or wait defensively. This creates a cross-versus-wait dilemma that may increase interaction uncertainty.

Characteristic 2: Risk Aversion.

Significant transitions to stopping during acceleration (VA→PS, Z=56.99) and turning (VT→PS, Z=47.32) suggest that pedestrians tend to follow a safety-first strategy under kinetic-energy or trajectory-uncertainty threats.

Characteristic 3: Efficiency Orientation.

Once safety is confirmed, interactions rapidly shift toward minimizing crossing time. Strong transitions from pedestrian stop to vehicle motion (PS→VK, Z=74.75; PS→VA, Z=63.52) and vehicle stop to pedestrian passage (VS→PA, Z=53.34; VS→PT, Z=79.89) demonstrate swift, complementary passage adjustments that prevent static stalls and reflect system-level efficiency.

Characteristic 4: Dynamic Right-of-Way Negotiation.

Passage rights are continuously negotiated through bidirectional behavioral coupling rather than unilateral yield/rush decisions. Strong reciprocal links (PS→VK, Z=74.75; VK→PS, Z=71.56; PA→VK, Z=72.15; VK→PA, Z=69.80) form a “negotiate - confirm - proceed” loop. This aligns with spatial-sharing frameworks and encounter-based interaction models, confirming that AV-pedestrian dynamics rely on implicit, mutually regulated gap negotiation.

5. Conclusions

This study applies Lag Sequential Analysis (LSA) to the nuScenes dataset, modeling AV-

pedestrian interactions as discrete state sequences to identify stable behavioral chains, such as “vehicle steady motion → pedestrian hesitation” and bidirectional vehicle–pedestrian negotiation chains. These patterns reveal four core interaction dynamics—intent uncertainty, risk aversion, efficiency orientation, and dynamic right-of-way negotiation—advancing interaction representation from instantaneous metrics to verifiable temporal sequences. By establishing a data-driven framework for sequential evolution, this work provides empirical grounding for future interaction modeling. However, the analysis is constrained by its focus on dyadic scenarios and the loss of fine-grained motion features inherent to trajectory discretization. Future research will address these limitations by extending LSA to multi-agent systems to capture collective behaviors, exploring higher-order lag structures for long-term dependencies, and integrating significant behavioral chains as structured priors or reward functions in prediction and planning models, with simulation and real-world validation to enhance traffic safety and efficiency.

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