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Construction of All-Weather Speed–Spacing Safety Benchmarks for Highways under Complex Weather Conditions Using FT-Transformer

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Abstract: To address the limited adaptability of static speed and spacing regulations under complex weather conditions, this study develops a data-driven framework for constructing all-weather speed–spacing safety benchmarks for highways. A total of 54 composite weather–traffic scenarios were generated through driving simulation experiments by combining weather and road surface conditions, visibility levels, illumination conditions, and background traffic flow. Microscopic driving behavior data were extracted to characterize the probabilistic distribution of vehicle speed and car-following distance under different environmental constraints. A multi-task FT-Transformer model combined with conditional quantile regression was employed to estimate the 15th, 50th, and 85th percentile boundaries of the two-dimensional safety interval. The 85th percentile boundary was further integrated with physical headway constraints and statutory speed–spacing requirements to generate scenario-specific safety benchmarks. The results show that the proposed model achieves competitive prediction accuracy and provides smoother responses under continuous visibility variations compared with tree-based baselines. Benchmark analysis indicates that low-adhesion snowy conditions require greater speed reductions than those implied by visibility-based statutory limits, while extreme low-visibility and high-traffic scenarios require larger car-following distances than the statutory minimum. These findings provide quantitative support for dynamic speed control, spacing management, and cooperative vehicle–infrastructure safety applications under adverse weather conditions.

1. Introduction

With the continuous growth of highway traffic volume, extreme weather conditions such as low visibility and snowy or icy roads significantly affect driving safety[1-3]. These conditions not only increase drivers' perceptual workload but also directly influence vehicle control behavior and traffic flow stability, leading to a substantial increase in rear-end collision risk. Traditional static traffic regulations and speed limits based on single visibility thresholds exhibit limited adaptability under dynamic traffic and weather conditions[4-6]. Consequently, dynamic speed and car-following distance control based on multi-source perception has gradually emerged as an effective strategy to enhance highway traffic safety.

Previous studies have primarily focused on analyzing driver behavior characteristics under low-visibility conditions, including lane deviations, delayed reactions, and speed adjustments, while also exploring dynamic speed limits and car-following control strategies[7]. However, existing methods mostly rely on macroscopic traffic flow data or kinematic models, which are insufficient for capturing individual driver behavior, limiting their ability to precisely quantify safe driving speeds and car-following distances under complex weather conditions[8, 9]. This limitation hinders the practical application of dynamic traffic management strategies on highways.

In recent years, deep learning and big data techniques have been widely applied to vehicle trajectory prediction and microscopic driving behavior modeling[10-12]. Notably, Transformer-based models have shown strong capability in modeling long temporal sequences and capturing global feature interactions, providing a useful tool for representing driver behavior under complex weather conditions and supporting dynamic driving risk assessment[13, 14].

Based on this background, this study proposes a data-driven framework for constructing all-weather speed－spacing safety benchmarks for highways under complex weather conditions. The framework uses an FT-Transformer model with conditional quantile regression to estimate the probabilistic safety boundaries of vehicle speed and car-following distance, and further transforms the predicted boundaries into scenario-specific control benchmarks by incorporating physical headway requirements and statutory speed－spacing constraints.

The main contributions of this study are threefold. First, a two-dimensional probabilistic safety interval of vehicle speed and car-following distance is formulated to describe heterogeneous driving responses under coupled weather, visibility, illumination, and traffic-flow conditions. Second, a multi-task FT-Transformer combined with conditional quantile regression is developed to estimate defensive safety boundaries while preserving the coupling relationship between speed and spacing. Third, a model－physics－regulation fusion strategy is proposed to transform the predicted 85th percentile boundaries into all-weather safety benchmarks, enabling a systematic comparison with existing statutory speed and spacing requirements.

2. Experimental Design and Data Acquisition

2.1. Construction of Composite Weather Scenarios and Driving Simulation

Table 1. Parameter settings for composite weather scenarios

Environmental Dimension	Levels	Parameter Setting	Physical/Visual Mapping
Weather & Road Surface	3	Fog, Rain, Snow	Friction coefficient μ = 0.8, 0.5, 0.25
Visibility Level	3	V1 (200 m), V2 (100 m), V3 (50 m)	Slight, moderate, severe visibility restriction
Illumination	2	Day, Night	Adequate ambient light / front-lamp only
Background Traffic Flow	3	Low, Medium, High	Free flow, synchronized flow, congested flow density

To investigate the effects of multi-dimensional weather coupling on driving behavior, a human-in-the-loop simulation experiment was conducted using the UC-win/Road driving simulation platform. The experiment adopted a factorial design, selecting four key environmental variables: weather and road surface conditions, visibility level, illumination, and background traffic flow. By crossing these factors, 54 composite traffic scenarios were generated, covering a wide range of conditions from normal traffic to extreme weather (Table 1).

A total of 20 licensed C1 drivers (12 males, 8 females; aged 20 – 26; 1 – 5 years driving experience; with normal vision and no history of accidents or motion sickness) participated. This sample provided controlled experimental observations for analyzing driving responses under low-visibility conditions, although its representativeness for the broader driving population remains limited.

2.2. Extraction and Preprocessing of Microscopic Trajectory Features

During the simulation, the system recorded vehicle microscopic motion states at a frequency of 10 Hz, including time index (t), vehicle speed (V), longitudinal and lateral accelerations (A), pedal operation, and longitudinal car-following distance (D).

To ensure data quality and remove unnatural behaviors, the following preprocessing steps were applied: (1) elimination of low-speed stationary states ($V \leq 5$ km/h) and abnormally short car-following distances ($D \leq 2$ m); (2) removal of non-car-following states that violated microscopic constraints ($D \geqslant 250$ m); and (3) application of linear interpolation to fill missing data, mapping categorical environmental labels to numerical physical quantities.

After preprocessing, a structured trajectory dataset was generated for subsequent multi-dimensional feature interaction analysis and construction of the two-dimensional probabilistic safety interval.

3. Methodology

3.1. Physical Definition of the Two-Dimensional Safety Interval

Traditional traffic safety thresholds usually rely on single kinematic extreme values, which are insufficient to describe the nonlinear distribution of driving behavior under complex weather conditions. In this study, a two-dimensional safety interval $\mathscr{I}_{\text{safe}}$ is proposed, defined as a two-dimensional probabilistic distribution over vehicle speed (V) and longitudinal car-following distance (D). The interval is constructed by extracting the central 70% of driving samples, and is formally expressed as:

$$I_{\text{safe}}=[V_{Q15},V_{Q85}]\times[D_{Q15},D_{Q85}] \tag{1}$$

where V_{Q15} and V_{Q85} denote the lower and upper bounds of safe driving speed, and D_{Q15} and D_{Q85} denote the minimum safe car-following distance and the defensive buffer distance, respectively. This safety interval provides a probabilistic reference for subsequent deep learning models, helping the predictions remain consistent with the observed distribution of experimental driving behaviors.

3.2. Deep Representation Learning and Multi-Target Prediction Based on FT-Transformer

The driving dataset contains both discrete categorical features, including weather, illumination, and traffic flow level, and continuous physical variables, including road friction coefficient, visibility, and traffic flow-related parameters. To unify heterogeneous feature dimensions, a feature tokenizer module is introduced to map discrete labels and continuous values into a unified feature vector. Subsequently, a multi-head self-attention mechanism is employed to capture the nonlinear coupling between vehicle motion states and environmental constraints.

Considering the significant individual differences among drivers under low-visibility conditions, conditional quantile regression (CQR) is incorporated to predict the probabilistic intervals of safe vehicle speed and car-following distance. The network uses an asymmetric loss function:

$$L_\tau(y,\hat{y})=\max\left(\tau(y-\hat{y}),(\tau-1)(y-\hat{y})\right) \tag{2}$$

By minimizing prediction errors at different quantile levels, the proposed method supports the estimation of probabilistic safety boundaries.

3.3. All-Weather Safety Benchmark Generation and Comparative Analysis

Based on the 85th percentile (Q_{85}) boundary, the predicted values ($V_{\mathrm{data}}, D_{\mathrm{data}}$) are compared with statutory limits ($V_{\mathrm{law}}, D_{\mathrm{law}}$) to generate dynamic control parameters:

$$V_{\mathrm{rec}}=\min\left(V_{\mathrm{data}},V_{\mathrm{law}}\right),\quad D_{\mathrm{rec}}=\max\left(D_{\mathrm{data}},D_{\mathrm{law}}\right) \tag{3}$$

In addition to statutory constraints, a basic physical headway requirement is introduced to avoid unrealistically small spacing recommendations under low-speed or sparse-sample conditions. The final recommended distance is therefore determined by jointly considering the predicted Q85 spacing boundary, the minimum statutory spacing requirement, and the physical headway-based spacing requirement.

This bidirectional truncation logic allows the recommended speed and car-following distance to balance data-driven predictions with regulatory constraints under extreme weather conditions, thereby supporting more conservative safety management.

3.4. Experimental Setup and Evaluation Metrics

To evaluate the effectiveness of the FT-Transformer model, it was compared with XGBoost, SingleTask ResNet, and the single-task FT-Base model. The network architecture consists of 4 layers, 8 attention heads, and an embedding dimension of 192. The AdamW optimizer was employed with a learning rate of 1×10^{-6} and a batch size of 16,384 samples.

Model performance was assessed from two perspectives: (1) deterministic accuracy, including mean absolute error (MAE), median absolute error (MedAE), and root mean squared error (RMSE); and (2) probabilistic interval quality, including prediction interval coverage probability (PICP), mean prediction interval width (MPIW), and Pinball loss. These six metrics were used to assess deterministic prediction accuracy and probabilistic interval quality for safe vehicle speed and car-following distance.

4. Results and Analysis

4.1. Model Prediction Performance and Physical Consistency

To evaluate the effectiveness of the proposed FT-Transformer architecture, the FT-Ours model was compared with XGBoost, SingleTask ResNet, and the single-task FT-Base model. The evaluation metrics included deterministic accuracy, represented by MAE, MedAE, and RMSE, and probabilistic interval quality, represented by PICP, MPIW, and Pinball loss. This evaluation setting was designed not only to compare point prediction accuracy, but also to examine whether the model can provide informative and compact safety intervals for speed and spacing control.

As shown in Table 2, FT-Ours achieves competitive deterministic accuracy compared with the baseline models. For car-following distance prediction, the MAE of FT-Ours is 19.021 m, which is slightly lower than those of XGBoost and SingleTask ResNet. For speed prediction, FT-Ours also obtains the lowest MAE among the compared models. Although the numerical differences in deterministic accuracy are relatively small, FT-Ours provides a more balanced interval performance by maintaining coverage close to the target prediction interval while controlling interval width and Pinball loss. These results suggest that the main advantage of the proposed model lies not only in marginal accuracy improvement, but also in its ability to jointly estimate speed – spacing safety boundaries with consistent probabilistic behavior.

Table 2. Comparison of model performance across prediction metrics

Model	Task	MAE ↓	MedAE ↓	RMSE ↓	PICP (%)	MPIW	Pinball ↓
FT-Ours (Final)	Distance (m)	19.021	4.333	42.69	72.69	41.96	7.909
FT-Base	Distance (m)	19.022	4.467	42.614	70.08	41.72	7.907
XGBoost	Distance (m)	19.025	4.323	42.729	74.03	42.31	7.912
SingleTask	Distance (m)	19.039	4.491	42.545	76.18	42.81	7.912
FT-Ours (Final)	Speed (km/h)	2.219	1.085	3.52	76.51	7.56	0.883
XGBoost	Speed (km/h)	2.232	1.071	3.536	75.41	7.58	0.894
SingleTask	Speed (km/h)	2.247	1.081	3.568	78.32	7.88	0.904
FT-Base	Speed (km/h)	N/A	N/A	N/A	N/A	N/A	N/A

Regarding physical consistency, Figure 1 shows the two-dimensional scatter distribution of the predicted safe speed and car-following distance. The fitted relationship follows the nonlinear trend implied by vehicle braking and spacing requirements, indicating that the predicted outputs are not merely discrete label responses but are broadly consistent with traffic-engineering expectations. This consistency is important for transforming model predictions into operational safety benchmarks.

Figure 2 further compares the model response under a simulated continuous visibility gradient. The FT-Transformer produces a smooth surface as visibility changes, whereas the tree-based baseline tends to generate stepwise variations around discrete environmental levels. This difference is particularly relevant for dynamic speed and spacing control, because real-world weather conditions usually change continuously rather than abruptly between predefined categories. Therefore, the smooth generalization capability of FT-Ours provides additional support for its use in proactive traffic management and vehicle – infrastructure cooperative applications.

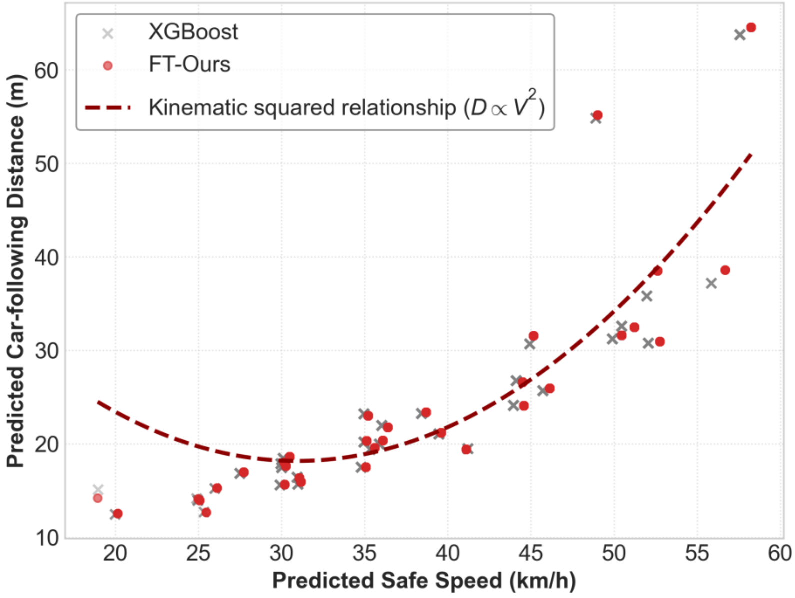

Figure 1. Scatter plot of predicted safe speed vs. car-following distance

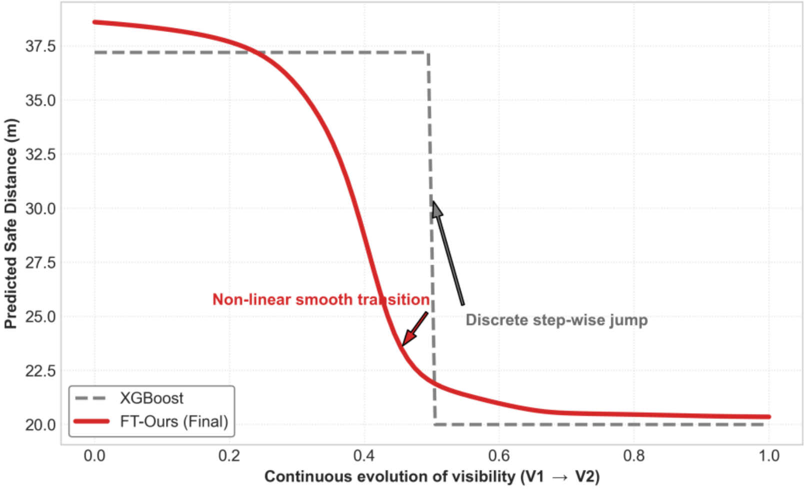

Figure 2. Smooth interpolated surface under visibility gradient simulation

4.2. All-Weather Safety Benchmark Generation and Regulatory Comparison

Table 3. Recommended safety benchmarks for typical traffic scenarios (daytime, medium traffic)

Weather	Visibility	Predicted Speed[Q15,Q50, Q85](km/h)	Predicted Distance [Q15, Q50, Q85] (m)	Legal Speed	Legal Distance	Recommended Speed	Recommended Distance	Recommended Headway(s)
Fog	V1	[54.7,58.2,60.3]	[29.0,64.6,166.1]	60	100	60	166	9.96
Fog	V2	[35.0,35.6,37.3]	[15.9,19.6,37.3]	40	50	37	50	4.86
Fog	V3	[17.9,18.9,21.3]	[8.3,14.2,93.0]	20	50	20	93	16.74
Rain	V1	[32.5,44.6,52.6]	[16.6,24.1,53.2]	60	100	53	100	6.79
Rain	V2	[30.1,31.1,31.6]	[13.1,16.3,90.5]	40	50	32	91	10.24
Rain	V3	[12.0,12.9,14.1]	[6.3,8.8,43.8]	20	50	14	50	12.86
Snow	V1	[26.8,38.7,41.9]	[15.8,23.4,50.4]	60	100	42	100	8.57
Snow	V2	[24.8,25.1,26.0]	[11.4,14.0,58.9]	40	50	26	59	8.17
Snow	V3	[11.7,12.1,13.8]	[5.9,12.4,83.9]	20	50	14	84	21.6

Based on the 54 composite weather scenarios, the generated all-weather safety benchmarks (Tables 3 and 4) reveal that speed and spacing regulations should not be evaluated independently. For instance, under conventional restricted-visibility scenarios, the statutory speed limit remains generally applicable, but the recommended car-following distance significantly exceeds the statutory minimum. Conversely, under low-adhesion snowy conditions, visibility-based statutory speed limits fail to capture the additional braking constraints caused by reduced road friction, necessitating lower recommended speeds. Furthermore, under extreme low-visibility and high-traffic scenarios, static minimum spacing requirements are insufficient to cover the risk associated with coupled adverse conditions. The proposed benchmark matrix therefore provides a scenario-specific supplement to existing regulations.

Table 4. Recommended safety benchmarks for extreme long-tail scenarios (nighttime, high traffic)

Weather	Visibility	Predicted Speed[Q15,Q50,Q85](km/h)	Predicted Distance [Q15, Q50, Q85] (m)	Legal Speed	Legal Distance	Recommended Speed	Recommended Distance	Recommended Headway(s)
Fog	V1	[20.3,49.0,53.8]	[7.5,55.1,138.8]	60	100	54	139	9.27
Fog	V2	[27.5,30.2,33.1]	[13.4,15.6,39.9]	40	50	33	50	5.45
Fog	V3	[12.9,13.0,14.7]	[6.0,7.3,54.2]	20	50	15	54	12.96
Rain	V1	[35.6,45.2,47.1]	[20.7,31.6,111.7]	60	100	47	112	8.58
Rain	V2	[23.8,25.0,26.2]	[11.2,14.1,30.4]	40	50	26	50	6.92
Rain	V3	[9.9,10.9,12.0]	[4.8,5.8,31.0]	20	50	12	50	15
Snow	V1	[31.1,35.1,36.9]	[16.2,20.3,49.8]	60	100	37	100	9.73
Snow	V2	[20.1,21.2,23.0]	[9.2,11.1,45.9]	40	50	23	50	7.83
Snow	V3	[9.8,10.0,11.1]	[4.9,7.1,75.9]	20	50	11	76	24.87

5. Conclusions

This study developed a data-driven framework to construct all-weather speed－spacing safety benchmarks. Results demonstrate that the proposed FT-Transformer achieves competitive deterministic accuracy and provides balanced probabilistic intervals with smooth responses under continuous visibility variations. Furthermore, the predicted speed－spacing relationships align with basic kinematic expectations, ensuring the physical plausibility of the generated boundaries.

The benchmark analysis further reveals that static speed and spacing regulations have different levels of adaptability under different weather－traffic combinations. Under conventional restricted-visibility scenarios, statutory limits can provide a useful baseline for safety control. However, under low-adhesion snowy conditions, the recommended speed can be lower than the statutory speed limit, indicating the need to incorporate road friction effects into dynamic speed management. Under extreme low-visibility and high-traffic scenarios, the recommended spacing can exceed the statutory minimum, suggesting that static minimum spacing requirements may not fully cover the risk associated with coupled adverse conditions.

Overall, the proposed benchmark framework provides quantitative support for dynamic speed control, spacing management, and cooperative vehicle－infrastructure safety applications under adverse weather conditions. Rather than replacing existing regulations, the framework can serve as a scenario-specific supplement for identifying when additional speed reduction or spacing expansion is required.

Several limitations exist. The safety boundaries rely on simulator-based trajectories from a demographically limited sample, requiring validation with real-world data. Additionally, benchmark values for sparse extreme weather scenarios partly depend on model-based interpolation. Future work will integrate large-scale naturalistic driving and vehicle-infrastructure data to validate the operational robustness of these benchmarks under real high-risk weather conditions.

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