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Lane-Change Intention Prediction Based On Non-Linear CRF

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Abstract:
Background*: Vehicle agent intention prediction is a fundamental time-series prediction task essential for enhancing autonomous driving systems. However, existing models often struggle to effectively capture global road scene information and the intricate interactions among multiple vehicles*
Materials and Methods*: To address these challenges, we propose a novel Nonlinear Conditional Random Field (Non-linear CRF) model, representing the first application of CRFs in the domain of vehicle agent intention prediction. The Nonlinear CRF exploits its unique capability to model agent interactions by incorporating both unary and binary potential functions. The unary potentials extract individual vehicle dynamics based on historical trajectories and road context, while the binary potentials leverage an attention mechanism to model the influence of local interactions among neighboring vehicles.*
Results*: Experiments conducted on the HighD dataset demonstrate the superiority of the proposed method over traditional approaches. These results underscore the model's ability to seamlessly integrate global perception with local interaction dynamics, enabling accurate and robust intention predictions in complex traffic scenarios.*
Conclusion: *By addressing critical limitations in existing methods, this study contributes significantly to advancing the field of autonomous driving and provides a robust framework for future research on time-series prediction in multi-agent systems.*
Key Word*: Intention Prediction; Time Series Prediction; Modern TCN; Conditional Random Fields; Non-Linear CRF.*

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I. Introduction

Autonomous Vehicles (AVs), as a critical component of intelligent transportation systems, play an essential role in ensuring road safety, alleviating traffic congestion, reducing energy consumption, and enhancing traffic flow efficiency. Thus, autonomous driving technology is widely regarded as a key enabler for the sustainable development of future transportation systems. However, despite significant advancements in autonomous driving technologies, existing onboard autonomous systems still face numerous challenges, particularly in environmental perception and decision-making processes. For example, obstacles and sensor limitations often restrict the system's perception of road traffic conditions to a localized view, adversely affecting its accuracy and robustness, as shown in figure 1. These issues become especially pronounced in complex traffic environments and high-density road scenarios, forming a major obstacle to achieving higher levels of automation (Level 4, L4) in autonomous systems [1].

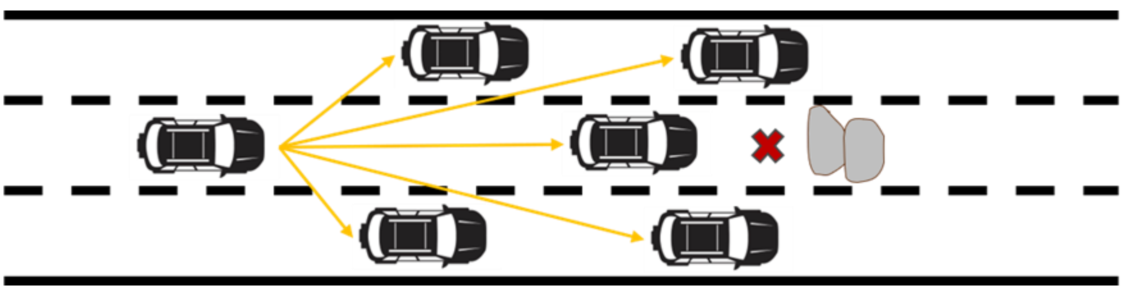

Figure no1: The Vehicle-Mounted Detector May Not be Able to Identify the Anomaly Due tto Occlusion

Comprehensive perception and in-depth understanding of traffic scenarios are crucial to addressing these challenges. Through global road scene perception, autonomous systems can acquire multi-dimensional information, including the dynamic states of vehicles, pedestrians, traffic signals, and other road participants. This global perception not only enhances the system's ability to recognize traffic environments more accurately but also improves its capacity to model the complex interactive behaviors between traffic participants. This modeling capability is critical for effectively predicting the behavioral intentions of various traffic participants (e.g., other vehicles and pedestrians) [1, 2]. Inspired by the concept of agent [3], which describes the agent as a system that is capable of flexible autonomous action in order to meet its objectives, this paper introduces the vehicle agent as the core modeling unit. The vehicle agent can be understood as cars and trucks with situational awareness and the ability to interact with other entities strategically, whether the awareness and the ability is from human driver or autonomous driving system. In this way, the concept of vehicle agent considers a and its operator as a whole. We then predict the intention of the agents. Intention prediction serves as a core component of autonomous driving decision systems. Accurate prediction of other road users' intentions is a prerequisite for safe and smooth navigation, particularly in multi-agent systems.

Moreover, precise intention prediction enhances not only the safety of autonomous systems but also their adaptability to traffic flows. Through long-term learning of driving behaviors and real-time inference, autonomous systems can interact more effectively with the surrounding environment. They can anticipate the behaviors of other vehicles or pedestrians and respond appropriately. For instance, accurately predicting a vehicle's turning intention at intersections, lane-changing behavior, or stopping intention can mitigate potential collision risks and optimize driving routes, thereby improving road efficiency and traffic safety.

However, existing intention prediction methods exhibit several limitations. Traditional rule-based approaches often rely on manually defined behavioral models, making them inadequate for handling complex and dynamic traffic scenarios [4]. On the other hand, deep learning-based methods (e.g., LSTM, Graph Neural Networks) are better at capturing complex non-linear relationships, but face challenges such as high computational costs and difficulties in ensuring prediction accuracy when dealing with multi-vehicle interactions and long-term dependencies [5]. In the meantime, the existing methods usually only model the interaction between the target vehicle and other vehicles adjacent to it [1, 6]. As a matter of fact, the behavior and interaction of a farther vehicle may also have an impact on the target vehicle and its surrounding vehicles, therefore, in order to improve the accuracy of the model, all vehicles in a certain road section should be taken into account in the modeling.

To make the task of intention prediction achieve better capture of global interaction and a lower computational complexity, we propose a novel vehicle agent intention prediction model based on a Conditional Random Field with non-linear structure (Non-linear CRF) for freeway scenarios. This model aims to combine global road scene information with local agent interaction data to provide more accurate prediction results. Unlike traditional single-agent modeling approaches, our Non-linear CRF method partitions road scenes into grids and constructs a predictive framework that simultaneously considers spatial structures and temporal dynamics. The model not only captures the behavioral intentions of individual vehicles but also accounts for interactions and local relationships among multiple vehicles, enabling precise modeling of multi-agent systems in complex traffic scenarios. This innovative approach represents the first application of Non-linear CRF to the problem of vehicle agent intention prediction. Compared with existing rule-based or deep learning methods, it offers superior integration of global and local information, enhancing prediction accuracy and real-time performance.

II. Related Work

Vehicle agent intention prediction, as a critical task in autonomous driving technology, aims to forecast the future behaviors of traffic participants (e.g., other vehicles and pedestrians) to ensure safe and efficient traffic decision-making. With the rapid development of deep learning techniques, data-driven models have achieved remarkable progress in vehicle agent intention prediction. Traditional rule-based approaches often depend on predefined behavioral models and expert knowledge, making them insufficient to address complex and dynamic traffic scenarios. In contrast, deep learning methods can automatically learn complex spatial and temporal dependencies from extensive historical data, thereby improving prediction accuracy and robustness.

Deep Learning-Based vehicle agent intention Prediction

In recent years, the continuous advancement of deep learning and causal inference techniques has driven significant progress in vehicle agent intention prediction.

Deep learning models play an essential role in this field. Researchers have leveraged high-dimensional data (e.g., high-resolution maps and sensor data) to train various deep learning models such as LSTM, SVM, and Transformers to predict vehicle agent intentions (e.g., driving straight, turning left, or turning right). For instance, Altché and de La Fortelle (2017) [7] and Kim et al. (2017) [8] were among the first to use LSTM-RNN models with past trajectories as input features to predict the future intentions of surrounding vehicles. Park et al. (2018) [9] employed an encoder-decoder LSTM model to predict future intentions, where the encoder encodes the past trajectories of surrounding vehicles, and the decoder decodes the occupancy grid map (OGM) for future intentions. A beam search algorithm was also applied to mitigate error propagation caused by the greedy strategy of the decoder LSTM.

Deo and Trivedi (2018a) [10] introduced a maneuver-based LSTM model that encodes the motions and interactions of surrounding vehicles to assign probabilities for each maneuver. The assigned probabilities enable multi-modal trajectory prediction. Although this approach achieved better RMSE results compared to state-of-the-art algorithms, its RMSE for long prediction horizons (PTH) remained high. While this algorithm accounted for vehicle interactions, it did not consider the dependencies among them. To address this limitation, Deo and Trivedi (2018b) [11] combined convolutional social pooling with encoder-decoder LSTM to predict maneuvers and future intentions. The convolutional social pooling learned the interactions and dependencies among surrounding vehicles. However, this algorithm had limitations, including fixed spatial grids in social tensors and a lack of consideration for visual contextual information. The authors compared performance with and without maneuver intention, revealing better results without maneuver consideration.

Luan et al. (2023) [12] utilized vehicle behavior and driver styles to predict future intentions. By analyzing historical trajectories of surrounding vehicles, they classified drivers as either aggressive or conservative. Predicted driver types were then used in a game-theoretic model to infer driver intentions. The identified vehicle behaviors and predicted driver intentions were input into two Nash optimization functions to predict integrated intentions. While adding driver information improved prediction, results could not be directly compared to state-of-the-art algorithms such as Li et al. (2019) [13] .

Despite these advancements, most models neglected the visual context of scenes, which is a critical factor influencing vehicle agent intentions. Zhao et al. (2019) [14] utilized interaction information between agents and scene contexts to predict future intentions. LSTM networks encoded the past trajectories of multiple agents, while CNN extracted feature vectors from scene contexts. Multi-Agent Tensor Fusion (MATF) networks fused LSTM and CNN outputs, and a fully connected network (FCN) predicted future intentions. Although this method considered visual contexts, it did not outperform algorithms like GRIP and ST-LSTM. Girase et al. (2021) [15] combined CVAE with Graph Neural Networks (GNN) for intention prediction, while Hu et al. (2022) [16] employed causal inference to analyze the relationship between driver behaviors and events, leveraging causal features for intention prediction. Furthermore, Yu et al. (2024) [17] extracted features such as lane-change incentives and driving styles using historical trajectory data for intention prediction.

Additionally, some studies focused on traffic scene image information, applying object detection methods to traffic participants before evaluating their intentions. For example, Li and Wang (2020) [18] developed a hybrid framework combining object detection and intention recognition to evaluate risks in complex traffic scenarios. Their approach achieved notable performance in detecting objects such as vehicles, pedestrians, and traffic lights, attaining 52.7% mean Average Precision (mAP) using YOLOv4 and the BDD100K dataset. For pedestrian intent recognition (crossing or non-crossing), they achieved an impressive 97.5% accuracy with VGG-19 CNN, while vehicle intent detection, such as braking and turning, reached 94% accuracy with EfficientNet CNN. Traffic light status recognition (e.g., red, green, or amber) yielded a 97.75% accuracy using MobileNet CNN. Despite these results, their reliance on simple braking and turn signal data proved insufficient to predict complex vehicle behaviors in scenarios involving sudden speed or direction changes, underscoring the need for more dynamic modeling approaches.

Large language models (LLMs) have also been applied to vehicle agent intention prediction. For instance, Peng et al. (2024) [19] used LLMs for intention prediction, incorporating chain-of-thought (CoT) reasoning to enhance explainability.

Rule-Based Approaches for vehicle agent intention Prediction

Apart from deep learning methods, rule-based approaches remain relevant in vehicle agent intention prediction. Because the accuracy and generalization ability of this kind of traditional methods are not as good as those based on deep learning, there are few researches in this field. For example, Lu et al. (2023) [20] used virtual vehicle control strategies to handle driver cut-ins, while Luan et al. (2023) [12] combined driver intention prediction and vehicle behavior recognition for lateral motion prediction of surrounding vehicles.

Overall, vehicle agent intention prediction is a vital technology for advancing autonomous driving systems. As research progresses, intention prediction methods will become more mature, offering robust support for the safe and efficient operation of autonomous vehicles.

Time Series Prediction

The field of time series prediction has seen significant advancements in recent years, driven by its critical applications across diverse domains such as finance, cloud systems, storage systems, environmental monitoring, and industrial processes. Researchers have introduced innovative methods to enhance prediction accuracy and efficiency, addressing unique challenges in different contexts.

A key trend is the integration of advanced labeling and preprocessing techniques to tackle data-specific issues. For instance, methods like continuous trend labeling [21] and feature preprocessing approaches to mitigate look-ahead bias highlight the emphasis on improving data reliability for financial forecasting.

Another notable direction is the development of specialized algorithms for multidimensional and chaotic time series, exemplified by the multidimensional KNN algorithm [22] and Time Convolution Neural Networks [23]. These approaches demonstrate a shift toward addressing the inherent complexity of time series data through tailored computational techniques.

Deep learning remains at the forefront of innovation, with models like integrated deep learning methods for cloud workload prediction [24], Read-first LSTM-based Encoder-Decoder models for air pollutant prediction Zhang et al.(2021) [25], and BiLSTM-based adaptability exploration in financial prediction [26]. These studies underscore the versatility and adaptability of neural networks in capturing temporal patterns across various domains.

Additionally, transfer learning has emerged as a promising strategy, particularly for scenarios with limited data. Methods such as those proposed by Zhou et al. (2023) [27] for industrial processes leverage historical data effectively, bridging gaps where conventional methods may falter due to data scarcity.

Comparative evaluations, such as those conducted by Chandra et al. (2021) [28], highlight the growing interest in understanding model performance across different datasets and prediction horizons. This focus not only aids in model selection but also drives the development of robust, generalizable frameworks.

The current trajectory in time series prediction research suggests a continued emphasis on hybrid methods that combine deep learning, statistical techniques, and domain-specific adaptations. Future efforts are likely to focus on enhancing model interpretability, improving real-time adaptability, and addressing challenges posed by complex, noisy, or sparse datasets. These advancements will be pivotal in expanding the practical impact of time series prediction across emerging applications.

Non-linear Conditional Random Fields

Conditional Random Fields (CRFs) [29], as discriminative probabilistic graphical models, are widely used for sequence labeling tasks. Compared to Hidden Markov Models (HMMs), CRFs overcome the label bias problem and can incorporate richer features. Typically, CRFs are employed to solve the conditional probability distribution of label sequences Y given observation sequences X, under the assumption of linear chain structures.

Beyond linear chain representations, CRFs can also model interactions among variables in graph-structured random variables through non-linear dependencies. For instance, DenseCRF [30] was applied in image segmentation tasks, defining fully connected CRFs over entire pixel sets of images. This approach handled billions of edges, necessitating efficient approximate inference algorithms. Recently, Mutual CRF-GNN (MCGN) [31] leveraged CRFs to infer affinities in graph neural networks (GNNs) for few-shot learning, showcasing how CRFs provide probabilistic and principled structures for GNN affinity estimation. Furthermore, adaptive spatiotemporal graph neural networks (ASTCRF) [32] combined CRFs with GNNs to learn enhanced spatiotemporal embeddings for multivariate time series (MTS) prediction. By modeling dynamic spatial dependencies and integrating neural CRF layers, ASTCRF effectively captured complex patterns in MTS data.

Summary

The commonly used vehicle intention prediction methods currently involve CNN, LSTM, GNN and rule-based methods, but they all have certain shortcomings. For example, CNN lacks dynamic modeling capabilities, LSTM has serious long-term time series prediction error accumulation, GNN modeling is not real-time enough, and rule-based methods rely on manually designed rules and have weak generalization capabilities. The fundamental problem is that it is difficult for them to model the entire traffic scene from a global perspective, which will lead to the omission of important information, thus affecting the reliability of the prediction.

The non-linear CRF model used for tasks such as image segmentation and small sample learning (although the models suitable for different specific tasks have some structural differenc es) can also be applied to the traffic scene studied in this article. Because they have in common that they can all be modeled as probabilistic graph models with nonlinear chain structures, and the key is to explicitly model the information transmission between nodes or the interaction between agents (this information is usually implicit in the state of the agent), CRF can solve this problem very well. In addition, CRF can also achieve dynamic modeling and real-time prediction, which is also its superiority. Therefore, we use ModernTCN for temporal prediction and non-linear CRF to integrate the temporal prediction and the interaction.

III. Method

Problem Modeling

We focus on multi-agent vehicle lane-change intention prediction in freeway traffic scenarios, which is a problem of time series prediction with interaction. Vehicles are modeled as agents whose decisions are influenced by road environments and the behavior of neighboring vehicles. vehicle agent intentions are classified into three categories: left lane change (LLC), lane keeping (LK), and right lane change (RLC). By modeling historical trajectory data, road structure information, and inter-vehicle interactions, we aim to predict the future lane-change intentions of the target vehicle.

To describe interactions among agents, we define the traffic scenario within a certain road segment as a graph structure

$$G = (V, E),$$

where nodes V represent vehicles, each containing trajectory and lane information for the target vehicle agent, and edges E represent adjacency relationships (i.e. neighboring) between vehicles. Two vehicles are considered adjacent if their distance is below a threshold d.

The temporal setup is as follows: the observation time window is $\{-n, -n+1, \ldots, 0\}$, with each time step interval t. The historical trajectory of the target vehicle i is represented as $I_i = (X_i, Y_i)$, where:
Apart from the vehicles' own historical trajectories, some other important features are also needed to model the state of vehicles. We choose the average speed of the vehicle in the observation time window and the lane distribution ahead together with the trajectory to build a complete scene of a single vehicle by concatenating them together as a feature vector.

Based on the observed vehicle and environment information, we predict the intentions of all vehicles within a future time window.

Non-Linear CRF Framework

We propose a vehicle agent intention prediction model based on a Non-linear Conditional Random Field (Non-linear CRF), designed specifically to model interaction graphs in multi-agent systems.

In complex traffic scenarios, vehicle behavior and intention are often significantly influenced by neighboring vehicles. For example, in lane-change scenarios, the decision of the target vehicle depends not only on its historical trajectory and lane information but also on the dynamic interference from adjacent vehicles' speed, position, and behavior. Such Non-linear mutual influences are challenging to accurately describe using traditional linear models. Non-linear CRF leverages unary and binary potential functions for joint modeling, considering both individual vehicle characteristics and the interactions between adjacent vehicles, thus improving the accuracy of intention prediction.

Specifically, the core of Non-linear CRF lies in using unary potential functions to describe individual vehicle behaviors and their relationship with the environment, while binary potential functions model the interaction characteristics between vehicles. Finally, a global energy function integrates multiple influencing factors, forming a comprehensive prediction of the target vehicle's intentions. Compared to traditional linear CRFs, Non-linear CRF employs more flexible energy function designs, making it better suited for diverse traffic scenarios. The global energy function comprises unary and binary potential functions, expressed as:

$$E(X|I) = \sum_{i} \psi_u (x_i) + \sum_{(i,j)\in E} \psi_b \left(x_i, x_j\right),$$

Where E represents the set of adjacency relationships between vehicles which is defined in section 3.1. For the neighbor vehicle selection strategy of the binary potential function, we constructed a fully connected scene graph (i.e., a probabilistic undirected graph in CRF) in the actual experiment, that is, all other vehicles in the scene are regarded as neighbor vehicles of the target vehicle. Then the posterior probability $\mathrm{P}(X|I)$ is maximized:

$$\mathrm{P}(X|I) = \frac{1}{Z(I)} \exp\left(-E(X|I)\right),$$

and $Z(X)$ is a normalization factor ensuring the validity of the probability distribution.

The intention prediction process for all vehicles is as follows:

Feature Extraction: Extract feature representations for each node (vehicle) based on historical trajectories, lane information, and the dynamic state of adjacent vehicles.

Node Potential Prediction: Employ ModernTCN to model the temporal characteristics of the target vehicle, predicting future potential states and intention probability distributions using unary potential functions.

Adjacency Relationship Modeling: Use binary potential functions and attention mechanisms to model interaction relationships between the target vehicle and adjacent vehicles, capturing their impact on the target vehicle's intentions.

Global Energy Function Construction and Inference: Combine unary and binary potential functions to construct a global energy function. An optimization algorithm is then applied to infer the final intention prediction for the target vehicle.
Figure 2 shows the overall framework of non-linear CRF.

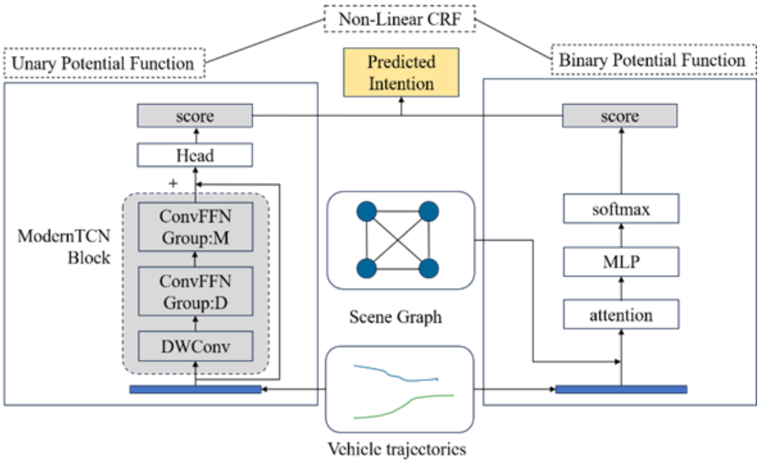

Figure no2: The Framework of Non-Linear CRF

Unary Potential Function

The unary potential function primarily extracts dynamic behavioral characteristics of individual vehicles from historical trajectory data. Modern Temporal Convolutional Networks (ModernTCN) [33] are employed to address this temporal prediction problem effectively. Specifically, ModernTCN leverages a fully convolutional architecture, inspired by Computer Vision (CV) techniques, replacing Transformer's self-attention layers with depthwise separable convolutions (DWConv) and utilizing convolutional (ConvFFN) for token mixing, whose structure is shown in Figure 3.

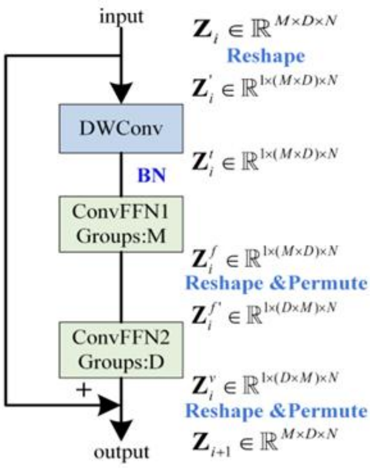

Figure no3: The Framework of a ModernTCN Block.

The vehicle's historical trajectory data is first input into ModernTCN:

$$h_i = \mathrm{ModernTCN}(X_i, Y_i)$$

where h_i represents the feature vector of the vehicle based on its historical trajectory given by ModernTCN. Next, this feature vector is converted into classification information that CRF can handle, that is, the score of three types of intentions: changing lanes to the left (LLC), changing lanes to the right (LK), and changing lanes to the right (RLC). This step is implemented using a linear layer:

$$\psi_u(x_i) = \mathrm{Linear}(h_i)$$

Binary Potential Function

The binary potential function plays a pivotal role in modeling the mutual influence between the target vehicle and its adjacent vehicles. To capture the global interaction effect, all of the other vehicle agents are defined as "adjacent vehicles". It captures complex local interaction dynamics, which are crucial for accurate intention prediction in multi-agent systems. For instance, neighboring vehicles' speed, position, and behaviors significantly affect the target vehicle's decision-making in lane-changing scenarios.

We adopt an attention mechanism to dynamically quantify the influence of neighboring vehicles on the target vehicle's intentions. The modeling process involves three detailed steps: calculating attention weights, aggregating neighboring vehicle features, and generating energy values.

Attention Weight Calculation

Attention weights quantify the influence of neighboring vehicle on the target vehicle. These weights are derived using a scoring mechanism based on the feature vectors:

$$\mathrm{Score}(v_i, v_j) = v_j^T W_a v_j$$

where W_a is a learnable attention matrix, and v_i and v_j denotes feature vectors of the vehicles which are concatenations of their trajectories. The attention scores are then normalized using a softmax function:

$$a_{ij} = \frac{\exp\ (\mathrm{Score}(v_i, v_j))}{\sum_{k\in N(i)} \mathrm{Score}(v_i, v_k)}$$

where $N(i)$ is the set of neighboring vehicles. This ensures that the sum of all attention weights for a given vehicle is equal to 1, allowing for an intuitive interpretation of influence distribution among neighboring vehicles.

Feature Aggregation

Once attention weights are calculated, they are used to aggregate features from neighboring vehicles. The aggregated feature vector for the target vehicle is computed as:

$$z_{ij} = \sum_{j\in N(i)} a_{ij}\, v_j,$$

where each neighbor's feature is weighted by its corresponding attention weight. This operation generates a comprehensive representation of the local interaction dynamics affecting the target vehicle.

Energy Value Generation

The aggregated features are then processed through a multi-layer perceptron (MLP) to produce the binary potential values. The energy function for the binary interaction between vehicles and is expressed as:

$$\psi_b(x_i,\ x_j) = -\,\mathrm{Softmax}(\mathrm{MLP}(\ Z_{ij})),$$

where z_{ij} denotes the concatenation of the aggregated feature representations of vehicles. The MLP maps these combined features into a scalar energy value that quantifies the interaction strength.

By integrating these steps, the binary potential function effectively captures the nuanced influence of local interactions in complex traffic scenarios, enhancing the overall predictive capability of the model.

Loss Function

From the scores of the unary and binary functions, we can calculate the probability distribution of a single agent:

$$\mathrm{P}(x_i) = \psi_u(x_i) + \sum_j \psi_b(x_i,\ x_j)$$

We use KL divergence as the training loss. Let the probability distribution of the predicted intention of a single agent be P, and the true probability distribution be Q, then our loss function can be expressed as:

$$L_i = D_{KL}(\mathrm{P}_i||\mathrm{Q}_i) = \sum_k \mathrm{P}(k)\ \ln\frac{\mathrm{P}(k)}{\mathrm{Q}(k)},$$

Then the total loss can be defined as the sum of the losses of all of the agents:

$$\mathrm{L} = \sum_i L_i$$

IV. Experiments

Dataset

The experiments in this study are performed on a primary dataset, HighD [34].

The HighD dataset, released by the Institute of Automotive Engineering at RWTH Aachen University, Germany, is a large-scale naturalistic vehicle trajectory dataset captured on German highways. Data was collected by a static drone over a section of (as shown in 5) from six distinct locations near Cologne, Germany, with variations in lane numbers and speed limits. The dataset includes a diverse range of vehicle types, such as passenger cars and trucks, along with metadata specifying vehicle attributes (e.g., length, width, type), trajectory timestamps, vehicle IDs, position coordinates, speed, and acceleration. It features 11.5 hours of measurements across six sites, with a total of 110,000 vehicles covering a combined travel distance of 45,000 km. Additionally, the dataset includes 5,600 detailed lane-change records.

Using advanced computer vision algorithms, the localization error in HighD data is typically under 10 cm. The dataset has a frame rate of 25 Hz, making it suitable for tasks such as driver model parameterization, autonomous driving, and traffic pattern analysis. To simulate realistic highway environments, the dataset also provides blank road images for each scene, enabling the overlay of vehicle trajectories and other visualization elements for more immersive representations.

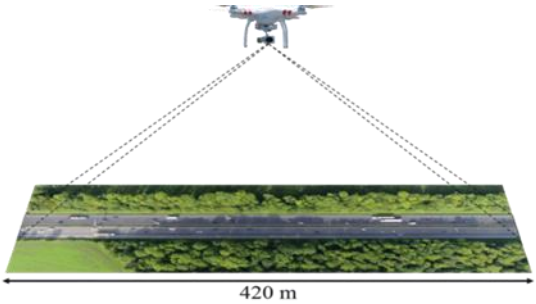

Figure no4: The Highd Dataset is a New Dataset of Naturalistic Vehicle Trajectories Recorded on German Highways Collected with a Drone.

In the data pre-processing stage, the data set is divided into "scenes". A "scene" refers to a collection of vehicle trajectories passing through a specified road section in a specified time period. After pre-processing the dataset, we find that there is an 8:1:1 imbalance in the samples of LK, LLC, and RLC in the dataset. We construct the training set of sample balance by resampling. By screening scenes with more lane change operations, the sample categories are balanced. Then we divide the validation and test sets. The ratio of the training set, validation set, and test set is set to 7:2:1.

For this study, the frequency of trajectory data is discussed and finally set to 5 Hz, and the observation window is set to 0.8 seconds. Trajectory coordinates are set by reference to the coordinate system of the data set. As shown in figure 5, the x-axis is along the road and the y-axis is perpendicular to the road.

Figure no5: The Coordinate System of HighD Dataset

Experimental Setup

The model was implemented using PyTorch and trained for 20 epochs on an NVIDIA A100 GPU with 48 GB of memory. The Adam optimizer was employed with a batch size of 512 and an initial learning rate of 0.002. An exponential decay rate of 0.9999 was applied to the learning rate at the end of each epoch to ensure stable convergence.

The training and evaluation procedures involved splitting the dataset into training, validation, and testing subsets. Standard metrics such as accuracy, precision, recall, and F1-score are used to assess the prediction performance for each intention category (left lane change, lane keeping, and right lane change). Additionally, Macro-F1 is calculated to provide a holistic measure of the model's overall performance across all intention categories.

By leveraging robust computational resources and a well-defined experimental pipeline, the proposed method's efficacy is rigorously validated under real-world traffic conditions.

Evaluation Metrics

To comprehensively evaluate the performance of the proposed model, we employ the following metrics for each intention category:

Precision (P): Precision measures the proportion of true positive predictions among all positive predictions made by the model. It is defined as:

$$PR = \frac{TP}{TP + FP},$$

where TP represents true positives and FP represents false positives.

Recall (R): Recall measures the proportion of true positive predictions among all actual positives. It is defined as:

$$RE = \frac{TP}{TP + FN},$$

where FN represents false negatives.

F1-Score: The F1-Score is the harmonic mean of precision and recall, providing a balanced metric for evaluating classification performance. It is calculated as:

$$F_1 = \frac{2PR * RE}{PR + RE},$$

To assess the overall performance across all intention categories, we compute Macro-F1 as the unweighted average of the F1-scores for each category:

$$\text{Macro} - F_1 = \frac{1}{3}\sum_{i=1}^{3} F_{1i}$$

where F_{1i} is the F1-Score for category.

These metrics ensure a thorough evaluation of the model's effectiveness, particularly for imbalanced datasets where certain intention categories may dominate.

Results And Analysis

For raw data at 25 Hz, we down-sample it to 12.5Hz, 5Hz and 2.5Hz with linear interpolation to do intention prediction task for several times together with original frequency. We examine whether the model can predict the sampled data in real time through the average single frame processing time. Table 1 presents the performance comparison of different sampling frequency.

The results show that the proposed Non-linear CRF model achieves real-time performance for networks at a frequency of lower than 12.5Hz. Taking into account the time allowed for other operations, we finally select 5 Hz as the experimental frequency.

Table no1: Comparison on the performance of different sampling frequency.

Frequency	**Processing Time (ms)**	**Required Processing Time (ms)**	**Real-time Prediction**
25 Hz (Original)	69	40	×
12.5 Hz	62	80	√
5 Hz	57	200	√
2.5 Hz	54	400	√

Table 2 presents the performance comparison of the proposed model against baseline methods CNN [35], LSTM [36] and LSTM-RNN [8] on the HighD dataset. The results demonstrate that the proposed Non-linear CRF-based model consistently outperforms baseline models in key metrics such as Macro-F1, precision, and recall.

Table no2: Comparison on the performance of CNN, LSTM, LSTM-RNN and Non-linear CRF (our method) on vehicle agent intention prediction.

Model	**Precision**	**Recall**	**Macro-F1**
CNN	96.54%	96.62%	96.58%
LSTM	96.32%	96.29%	96.30%
LSTM-RNN	96.81%	96.73%	96.70%
Non-Linear CRF(Ours)	**97.31%**	**97.15%**	**97.23%**

The superior performance of the proposed model can be attributed to its ability to:

Capture Global and Local Dynamics: The integration of unary and binary potential functions allows the model to effectively incorporate both individual vehicle behaviors and interaction dynamics.

Leverage Advanced Feature Representations: ModernTCN provides robust temporal modeling, enhancing the accuracy of intention predictions.

Handle Complex Scenarios: The attention-based binary potential function enables the model to dynamically adjust to varying interaction strengths in different traffic scenarios.

These results highlight the potential of Non-linear CRF-based methods in advancing the decision and planning of autonomous driving by improving the accuracy and robustness of vehicle agent intention prediction in real-world environments.

V. Conclusion

We propose a novel vehicle agent intention prediction model based on Non-linear Conditional Random Fields (Non-linear CRF) in this study, specifically designed to address the challenges of multi-agent interaction modeling in complex traffic scenarios. By integrating global scene context with local vehicle interactions, the model effectively captures the dynamics of multi-agent systems and delivers highly accurate intention predictions.

Experimental results on the HighD dataset validate the effectiveness of the proposed model. The Non-linear CRF-based approach consistently outperforms baseline methods in terms of precision, recall, and Macro-F1 (for all of the intention types), showcasing its potential for decision and planning of autonomous driving. Therefore, the autonomous driving system can enhance security and efficiency in certain scenarios.

Our method is merely an intention prediction of an ideal situation, simplifying the real-world scenario to some extent. Future research could extend this work in the following directions:

Investigating how road geometry variations (e.g., 3-lane vs. 5-lane highways) and dynamic speed constraints impact intention prediction accuracy. This requires developing adaptive feature encoding mechanisms that automatically adjust to lane-dependent interaction patterns, speed-regulated temporal receptive fields, weather-induced behavioral modifications, etc.

Current predictions focus on imminent maneuvers (5-10s horizon), yet strategic driving goals (e.g., target exits, route preferences) fundamentally shape tactical decisions.

Developing an end-to-end system (from raw data of scenarios to path prediction and planning) to bridge the current algorithm-data gap demands co-designing.

Overall, our study highlights the promise of Non-linear CRF-based approaches in advancing vehicle agent intention prediction, contributing to the development of safer and more efficient autonomous driving systems.

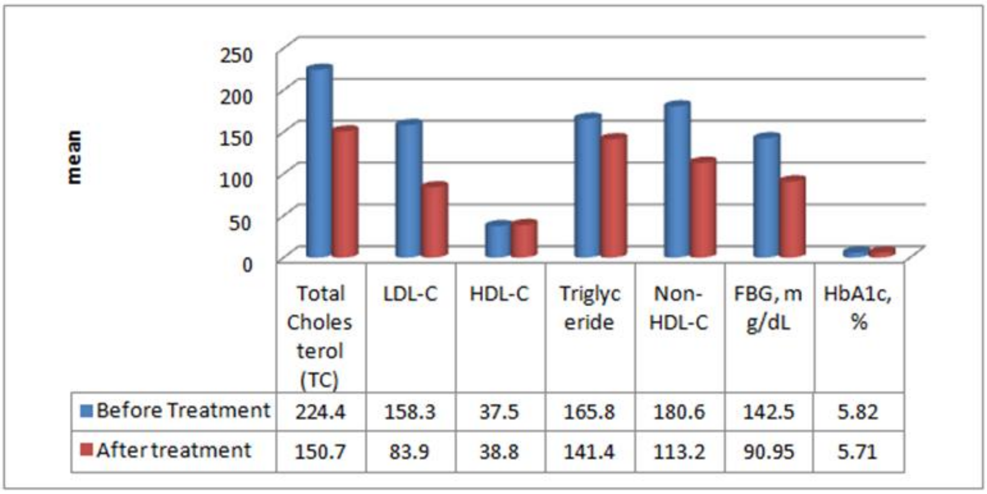

Table no3: Shows Percent Change in Lipids,(mg/dL) on a regular dose of Rosuvastatin 20mg for 6weeks. Total Cholesterol (TC)level reduced by(-26.49%), Low-density lipoproteins cholesterol(LDL-C) went down by (-37.28%), Triglyceride reduced to(-17.3%), Non-HDL-C went down by(-29.71%),after 6 weeks of medication. While there had been a reduction in the undesirable Lipids due to the above medication ,there was a positive upwards change in the desirable Lipids like high-density lipoprotein cholesterol (HDL-C) which improved by (+8.17%), Further, Fasting blood glucose, FBG, mg/dL level were reduced by (-37.95%). and HbA1c, % hemoglobin A1C test which measures blood sugar control over the preceding three months had also gone down by(-11.00%). The desirable alterations in respect of all the above parameters which were attributable to the above medication, were statistically significant, P<0.001---0.033.

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