AI-Assisted Maneuver Coordination for Connected and Automated Vehicles

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***Abstract*—Connected and Automated Vehicles (CAVs) represent a crucial step forward in the evolution of Intelligent Transport Systems (ITS), supporting enhanced communication, coordination, and decision-making among vehicles, infrastructure, and road users. Vehicle-to-everything (V2X) communication enables information sharing between road users and could be employed in various intelligent transportation scenarios. In particular, maneuver coordination is a fundamental aspect of cooperative driving and remains a key challenge for autonomous vehicles, as it requires consistent shared understanding and synchronized decision-making among multiple agents. This paper introduces an AI-assisted lane change maneuver coordination solution that integrates a maneuver coordination algorithm and an AI model. The AI model is designed to identify and restrict coordinations triggered by the algorithm that are predicted to fail. We demonstrate that integrating AI into maneuver coordination algorithms increases the coordination success rate regardless of traffic conditions and the accuracy of the trajectory predictions exchanged during coordination.**

***Index Terms*—maneuver coordination, intent-sharing, artificial intelligence, cooperative driving, connected and automated vehicles, CAV, V2X, vehicular networks.**

I. Introduction

One of the most promising applications of V2X connectivity lies in cooperative driving, where connected and automated vehicles can coordinate maneuvers to achieve safer, more efficient, and more predictable traffic interactions [1]. When a vehicle needs to perform a maneuver, such as a lane change, overtaking, or merging, the cooperation of one or more surrounding vehicles is often required to successfully achieve its objective. Given the need for consistent and interoperable mechanisms for maneuver coordination, standardization efforts have been initiated by major international organizations. In particular, the European Telecommunications Standards Institute (ETSI) and the Society of Automotive Engineers (SAE) have both undertaken work in this area. ETSI has focused on defining message content and communication protocols for maneuver coordination (ETSI TR 103578), while SAE is addressing aspects related to maneuver sharing and negotiation (SAE J3186). Maneuver coordination involves explicit interaction among vehicles to negotiate intentions and feasibility for a shared decision. Due to the highly dynamic and coupled nature of traffic, capturing all possible outcomes with deterministic algorithms is challenging, motivating more adaptive decision-making approaches. In this context, Artificial Intelligence (AI) is emerging as a powerful tool for analyzing information exchanged through V2X communication. In this work, we propose an AI-based maneuver coordination solution that integrates a maneuver coordination algorithm with an AI model. More precisely, the algorithm triggers new coordination processes, while the AI model acts as a decision filter, blocking attempts predicted to fail based on the driving context and ensuring coordinations occur under favorable conditions. The approach is particularly useful in scenarios where traffic interactions are highly dynamic and interdependent, making it impossible to capture all possible coordination outcomes with deterministic algorithms. To explore the full range of potential cases, this study considers both ideal and simplified vehicle trajectory predictions, coming from the intent sharing process [2]. While these predictions are not intended to directly mirror practical implementations, their analysis provides valuable insight into how maneuver coordination solutions can operate under both favorable (ideal prediction) and challenging (simple and inaccurate prediction) coordination conditions. In this study, the proposed solution is applied to the coordination of lane change maneuvers in highway scenarios. The results demonstrate that the approach enables safe and efficient maneuver execution while effectively handling the complexity of multi-vehicle interactions, leading to improved coordination performance under realistic traffic conditions. The remainder of this paper is organized as follows: Section II reviews related work and existing approaches to maneuver coordination. Section III describes the proposed framework architecture, detailing both the deterministic coordination logic and the integrated AI model. Section IV presents the experimental setup and validation results. Finally, Section V concludes the paper and outlines directions for future works.

II. Related Works

Maneuver coordination is a fundamental component in enhancing cooperative driving among connected and automated vehicles (CAVs). It enables vehicles to coordinate and execute maneuvers collectively, ensuring safety, efficiency, and predictability in dynamic traffic scenarios [3] [4]. To properly understand the design and reliability challenges involved, maneuver coordination can be conceptually decomposed into four main phases:

- Intention announcement, where a vehicle communicates its intended maneuver to surrounding vehicles;
- Feasibility assessment, in which vehicles evaluate whether the maneuver can be executed safely and efficiently in the current traffic context;
- Negotiation and agreement, where vehicles reconcile potential conflicts to reach a shared decision on maneuver execution;
- Execution and monitoring, during which the maneuver is carried out while continuously observing surrounding traffic to ensure coordination remains valid.

Defining these phases [5] [1] provides a structured view to analyze reliability and performance challenges, allowing each stage of the process to be examined in detail and highlighting both strengths and potential issues. For instance, certain phases such as negotiation, may be more sensitive to communication delays or interaction uncertainties, while others, such as the feasibility assessment, can be more influenced by the quality of data and algorithms adopted to perform the evaluation.

A. Design Approaches for Maneuver Coordination

Early studies focused on protocol-based coordination, where specific maneuvers are predefined and coordinated using deterministic rules [1]. State-machine or negotiation-based methods [6] explicitly represent all possible states and transitions during the negotiation and execution phases, providing solutions to identify potential errors and enhance reliability. Large-scale projects, such as the German IMAGinE project [7], demonstrate practical cooperative driving functions, including highway merging, lane changes, and overtaking maneuvers. These initiatives provide valuable insights into the complexities of real-world maneuver coordination, such as handling interactions among multiple vehicles, dealing with dynamic traffic conditions, and ensuring reliability and safety in large-scale deployments. Other approaches have emphasized decentralized coordination strategies, such as implicit and explicit coordination mechanisms, space–time reservation, and negotiation frameworks [4]. In contrast, trajectory-based approaches focus on coordinating maneuvers by sharing planned or desired motion information among vehicles [8]. Providing surrounding vehicles with information about one's expected future motion is referred to as intent sharing [2], an approach that is currently adopted in emerging cooperative driving and V2X standards. This capability is essential for maneuver coordination, as it enables vehicles to anticipate the future behavior and paths of their neighbors.

B. Challenges in Maneuver Coordination

Despite advances in cooperative maneuver design, existing coordination strategies have limitations when applied to complex multi-vehicle interactions. In [3], authors emphasize that cooperative maneuver negotiation protocols are an active research area with diverse unresolved challenges, indicating that simple strategies may not capture the full spectrum of real-world interaction complexities. In parallel, optimal control–based cooperative lane change studies demonstrate that coordinated approaches can significantly reduce traffic disruption and improve throughput compared to non-cooperative baselines [9], pointing to the potential gains from adaptive decision making in complex traffic scenarios.

Several studies [10] have examined maneuver-level cooperation methods based on explicit negotiation and reservation of road space, showing that coordinated maneuvers can reduce abrupt braking and improve safety in conflict scenarios without causing huge changes to surrounding traffic flow.

C. Motivation for AI-Driven Approaches

These challenges motivate the use of AI in maneuver coordination, enabling adaptive reasoning over dynamic interactions and supporting safe and efficient cooperative decisions. Prior work has explored the use of machine learning to support cooperative maneuvers, for instance, through centralized coordination systems that predict whether a vehicle can complete a lane merge and provide trajectory recommendations that account for surrounding traffic [11]. Complementary research has focused on improving the understanding of surrounding vehicle behavior through AI-based intention recognition and trajectory prediction [12]. These studies highlight how learning-based models can effectively capture complex interaction patterns and temporal dependencies that are difficult to model explicitly using deterministic approaches alone.

In this study, we focus on lane change maneuver coordination on highways, demonstrating how adaptive, AI-driven strategies can enhance the reliability and efficiency of coordination decisions under realistic and diverse traffic scenarios.

III. Lane Change Maneuver Coordination Framework

Figure 1 provides an overview of the proposed lane change maneuver coordination framework. The framework combines a deterministic maneuver coordination algorithm with an AI-based predictive layer, both of which are described in detail in the subsections below.

A. Deterministic Algorithm

Unlike isolated motion planning, maneuver coordination requires vehicles to consider not only their own objectives but also the feasibility and impact of the maneuver within the local traffic context. The successful execution of a maneuver often depends on the behavior and responses of surrounding vehicles. In this study, we refer to the ego vehicle as the Host Vehicle (HV), which intends to perform the lane change maneuver, and to a cooperating vehicle as the Remote Vehicle (RV), whose behavior may be adapted to facilitate the maneuver. An example of a lane change that can be managed by the algorithm is shown in Figure 2. In this scenario, the HV intends to change its current lane to the right one. However, the available gap is insufficient, so the objective of the maneuver coordination process is for the RV to decelerate and create the necessary gap following its negotiation with the HV. The maneuver coordination process considered in this study is implemented through a deterministic coordination algorithm

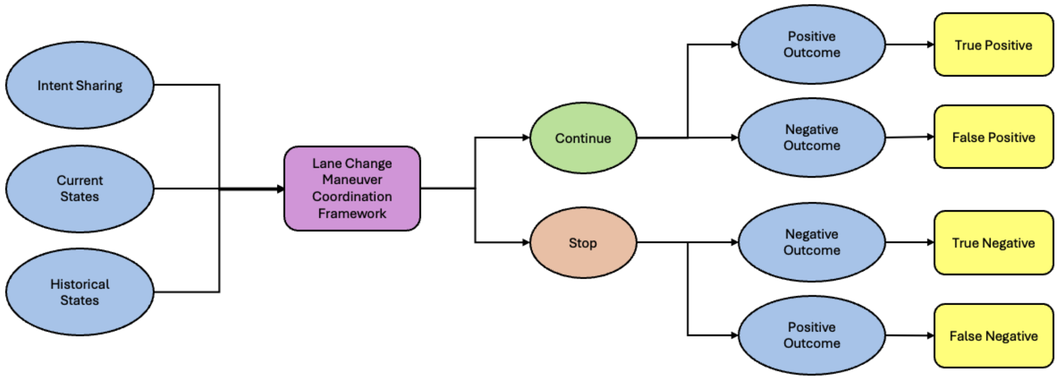


Fig. 1: Overview of the proposed framework architecture: Blue elements show data from simulation logs (input data and coordination outcomes). Purple components depict the maneuver coordination framework, consisting of a deterministic algorithm with the integration of XGBoost filtering. Green and red shapes show the evaluation results. Yellow rectangles represent metrics from AI-based filtering (TP, FP, TN, FN) computed from actual coordination outcomes.

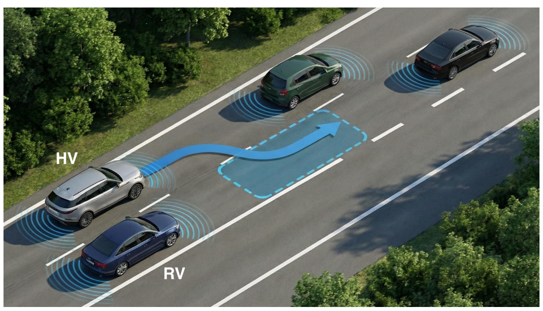


Fig. 2: Lane change situation in which the Host Vehicle (HV) needs a gap created by the Remote Vehicle (RV) to perform the desired maneuver.

that governs how the ego and cooperating vehicle interact and make coordination decisions. This algorithm relies on vehicle states and planned trajectories obtained through an intent-sharing process, in which all vehicles directly involved in a coordinated maneuver exchange their intended trajectories via V2X communication. Trajectory prediction in this context is inherently challenging due to the dynamic evolution of traffic and complex interactions among vehicles. To account for different levels of prediction accuracy, rather than relying on a single strategy, we consider two approaches in our study:

- Baseline trajectory prediction: future trajectories are computed assuming constant speed velocity.
- Ideal trajectory prediction: the exact future trajectories of all nearby vehicles are known, representing the upper bound of prediction accuracy.

Based on this information, the coordination decision follows a predefined sequence of steps:

1) The ego vehicle evaluates the incentive criterion for a lane change. A lane change is considered beneficial if switching to a target lane would yield a speed closer to the desired one. This evaluation relies on the minimum speeds of preceding vehicles in each lane obtained through V2X communication;
2) A comfort feasibility check is performed to assess whether the ego vehicle and the cooperating vehicle would experience longitudinal decelerations harder than $-2\ \mathrm{m/s^2}$ if the maneuver were executed by the ego vehicle in the current moment;
3) If the comfort criterion is not met, a short-horizon analysis of future traffic evolution (with a 6 s prediction horizon) is performed based on the trajectories exchanged through V2X, in which a predefined controlled deceleration is planned for the cooperating vehicle;
4) The longitudinal accelerations of the involved vehicles are computed from the planned trajectories, and the comfort criterion is then evaluated;
5) The lane change maneuver is considered feasible if there exists a future moment within the prediction horizon at which the comfort criterion is satisfied for both the ego vehicle and the cooperating vehicle. If no such moment exists, the maneuver is rejected;
6) In case the maneuver is considered feasible, coordination with the cooperating vehicle is initiated and the lane change is executed according to the determined timing and trajectory.

Once the maneuver is confirmed feasible, the maneuver coordination successfully progresses through a series of interaction phases between the HV and RV. If the HV initiates a maneuver, it enters the HV negotiation state, sending requests to the RV. The RV may accept, enter the RV Negotiation state, and reply until a confirmation is received. Upon successful negotiation, the HV executes the maneuver while the RV adjusts its trajectory with a deceleration to facilitate it. After execution or timeout, both vehicles return to their initial state, sharing their future intent with the neighbors. Coordination can fail during negotiation or execution. An unsuccessful negotiation may occur if HV's request messages, RV's response messages, or HV's confirmation messages are not received before the Negotiation Timeout, if the RV is already involved in another coordination as HV or RV, or if the HV executes the maneuver independently before negotiation completes. An unsuccessful execution may occur even after a successful negotiation if the maneuver cannot be completed within the Execution Timeout due to unexpected traffic conditions, or if the HV chooses a different maneuver. For specific implementation details of this deterministic algorithm, we refer to [1].

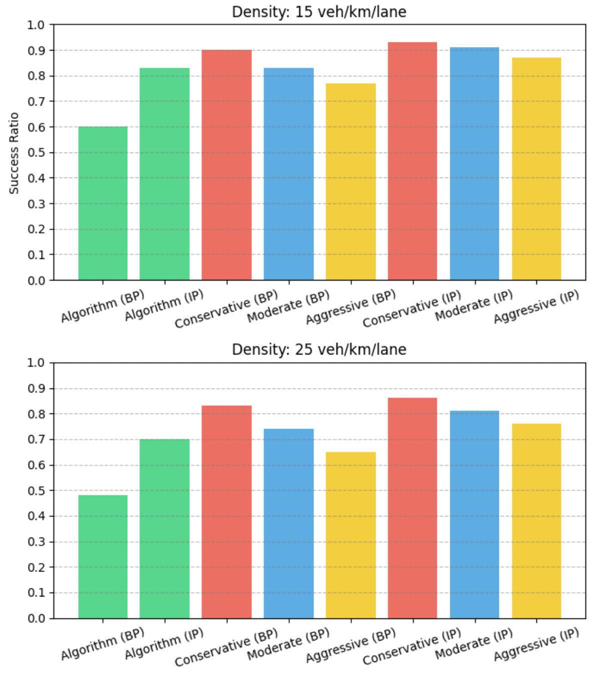
This deterministic algorithm provides a clear and structured mechanism for coordinating maneuvers under well-defined conditions. However, accurately anticipating the evolution of complex and highly dynamic traffic during a maneuver coordination process is challenging, and such evolution may affect both the feasibility and the benefits of a given coordinated maneuver. Enhancing the ability to foresee this evolution would improve the reliability of maneuver coordination.

B. AI Model

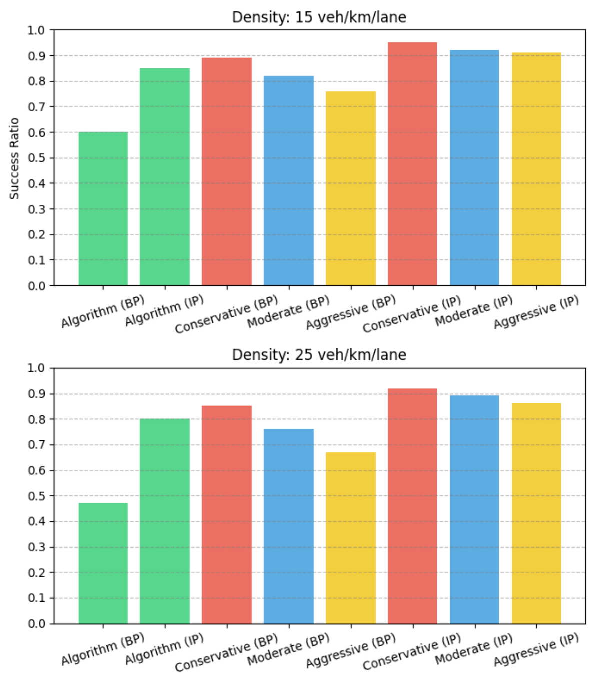
The AI model identifies coordination triggers, generated as outputs of the algorithm, that are likely to fail and prevents their execution. When a negative outcome is predicted, the coordination is not initiated. This integration enables the system to combine the interpretability and reliability of the maneuver coordination algorithm with the adaptability of data-driven learning, thereby enhancing the robustness and safety of the coordination process. Even when using precise trajectory prediction models, errors and unexpected changes in traffic conditions are unavoidable in real-world scenarios. From this perspective, a deterministic algorithm may fail to account for all possible dynamic variations, limiting its ability to guarantee successful maneuver coordination in highly dynamic environments. The AI model adds a predictive, adaptive layer to the deterministic framework, enabling real-time conflict anticipation and maneuver adjustment to enhance safety and efficiency. The input to the AI model focuses on the HV, RV, and the vehicles directly ahead of each, with structured features capturing their past, current, and anticipated future states. Specifically, the feature set includes (i) relative kinematics (e.g., distances and relative speeds), (ii) predicted future motion (e.g., future distances and speeds), (iii) historical motion information (e.g., past distances and speeds), and (iv) rule-based variables capturing interaction consistency between vehicles. These vehicles are chosen because their relative dynamics have the greatest impact on the feasibility and safety of a lane-change maneuver. This fixed selection of four vehicles ensures a consistent input size for the model, simplifying training and deployment. The output of the model is a binary decision indicating whether a proposed maneuver coordination should be executed or suppressed. A negative prediction effectively prevents the coordination from being initiated, allowing the AI to take precedence in the decision-making process over the deterministic algorithm. In this context, True Positives (TP) occur when the AI correctly allows a coordination that succeeds, while False Positives (FP) happen when the AI allows a coordination that ends up failing. True Negatives (TN) are cases where the AI correctly suppresses a coordination that would have failed, and False Negatives (FN) occur when the AI suppresses a coordination that would have succeeded. The model selected is the eXtreme Gradient Boosting (XGBoost) classifier, whose most widely used implementation is described in [13]. XGBoost is an optimized and scalable gradient boosting framework, which can employ various types of weak learners but is most commonly applied with decision trees. It builds an ensemble of trees sequentially, where each tree aims to correct the errors of the previous ones. It is widely adopted due to its computational efficiency, built-in regularization mechanisms, and ability to handle missing data and nonlinear relationships. XGBoost is particularly well-suited for decision-making tasks with structured inputs and discrete outputs, such as maneuver coordination, as tree-based ensembles naturally capture conditional patterns and decision logic inherent in the data. Compared to deep neural networks, these models typically require less extensive hyper-parameter tuning, offer greater transparency in their decision structure, and provide a favorable trade-off between predictive performance and computational efficiency, making XGBoost appropriate for safety-critical and real-time traffic applications. We noticed that the model, in its vanilla version, tends to overfit the training dataset, creating a huge performance gap between train and validation data. This is probably due to the high similarity among coordination scenarios in the highway environment. Most lane change situations share comparable spatial and temporal dynamics, which limits the model's ability to generalize and instead biases it toward exploiting repeated, scenario-specific regularities. In this case, XGBoost's built-in regularization mechanisms help alleviate overfitting. The L1 (Lasso) term encourages sparsity in the model by driving less relevant features toward zero, while the L2 (Ridge) term penalizes large weights to smooth the decision boundaries. Together, these hyperparameters enhance the model's robustness and generalization in the presence of highly similar lane-change coordination cases.

IV. Experiments

In this section, we validate the proposed framework by demonstrating how the decision-making process of a lane change maneuver coordination system, originally based on the deterministic algorithm described in Section III, can be enhanced with an AI-based predictive layer to improve the reliability of maneuver execution. This extension enables the system to be more robust to traffic changes that may occur between the time a trajectory is predicted and when it is executed. More generally, it helps the framework capture complex patterns that are difficult to replicate with a traditional deterministic algorithm. The simulation environment consists of a 5 km highway with 6 lanes (3 lanes in each direction). The scenario employs periodic boundary conditions, allowing vehicles that reach one end of the highway to re-enter the simulation from the opposite end. The simulation results are organized into two main categories based on the coordination avoidance range: 200 meters and 500 meters. The coordination



(a) Coordination avoidance range = 200 m.



(b) Coordination avoidance range = 500 m.

Fig. 3: Maneuver coordination success rate for different solutions combining the maneuver coordination algorithm and the AI model under different vehicular densities.

avoidance range defines the minimum distance ahead of the host vehicle (HV) within which additional coordination events are not allowed while the HV is engaged in its current maneuver, thereby ensuring sufficient space for the ongoing coordination. Increasing this range improves safety by providing a larger buffer, but it may also prevent some coordination opportunities that could benefit traffic flow, highlighting a trade-off between safety and efficiency. Within each category, the data is further divided into subgroups based on traffic density, respectively 15 and 25 veh/km/lane, and trajectory prediction methods described in III-B: baseline trajectory prediction and ideal trajectory prediction. These two prediction approaches are intentionally chosen as representative extremes, allowing us to analyze a broad spectrum of prediction performance without focusing on the specifics of any single strategy. Future trajectories are predicted by considering all vehicles within a range of 500 meters ahead of the HV. This structure enables comparative analysis of coordination performance across different spatial constraints, traffic conditions, and trajectory prediction methodologies.

Parameter	Value
Number of Estimators	700
Learning Rate	0.03
Max Depth	4
Lambda (L2 Regularization)	5
Alpha (L1 Regularization)	5
Feature Subsampling	0.7
Classification Thresholds	0.3, 0.5, 0.7

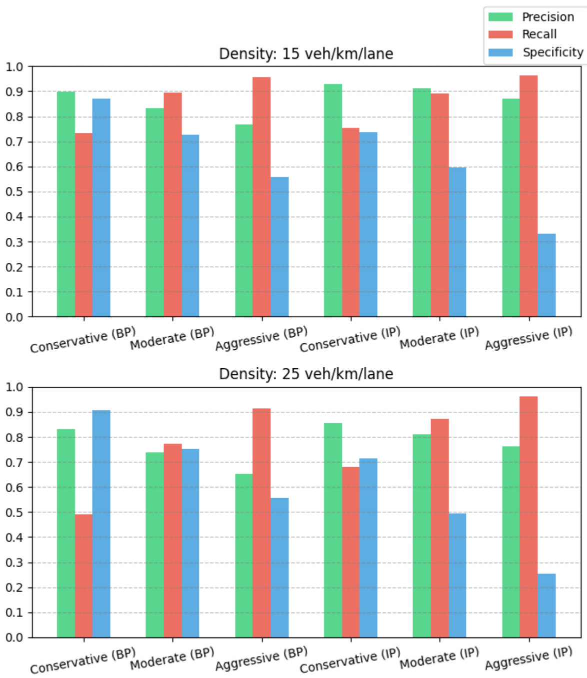
TABLE I: Hyperparameters for XGBoost Classifier

The resulting dataset is generated by running simulations in which CAVs rely exclusively on the deterministic lane change maneuver coordination algorithm, without AI support. The outcomes of these simulations are then used to label coordination events and build the dataset employed for training and testing the complete framework.

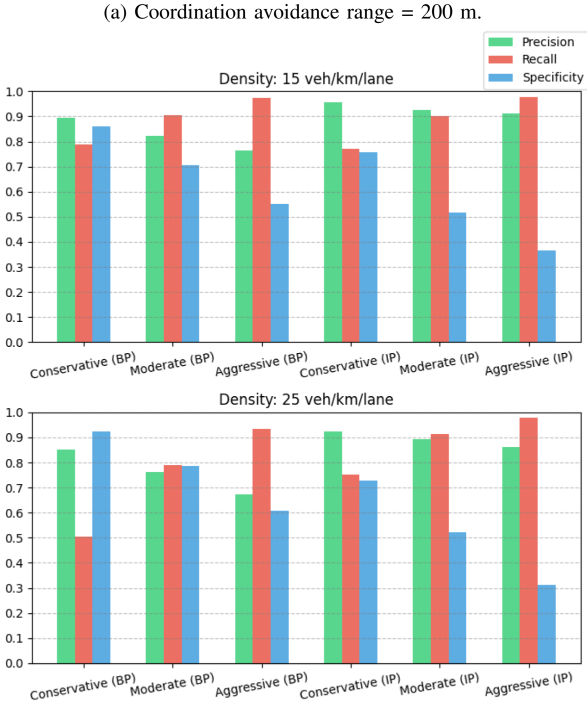
XGBoost classifier has been trained using the hyperparameters presented in Table I, which have been set after a hyperparameter search to identify the optimal configuration that maximizes the coordination success ratio, defined as the proportion of successful coordination events out of the total, while preventing overfitting. The selected parameters include 700 estimators with a conservative learning rate of 0.03, a maximum tree depth of 4 to control model complexity, and balanced L1 (alpha=5), L2 (lambda=5), and feature sampling (0.7) to enhance generalization and avoid overfitting. Three classification thresholds have been selected to evaluate performance under scenarios with varying levels of conservativeness in allowing maneuver coordination events. A threshold of 0.7 favors conservative behavior, ensuring that coordination is attempted only when the model exhibits high confidence in a successful outcome. Conversely, a threshold of 0.3 enables a more aggressive strategy, permitting a larger number of maneuver initiations at the cost of an increased failure rate, while a threshold of 0.5 represents an intermediate trade-off between these two extremes.

Performance across the different AI approaches (Conservative, Moderate, Aggressive) is evaluated using three standard classification metrics:

- Precision: the proportion of coordination opportunities



(a) Coordination avoidance range = 200 m.



(b) Coordination avoidance range = 500 m.

Fig. 4: Precision, recall, and specificity of the AI-assisted maneuver coordination framework across different classification thresholds and vehicular densities.

predicted as favorable that are actually favorable, defined as $\frac{\text{TP}}{\text{TP+FP}}$, which measures how reliable the model's positive predictions are.

- Recall: the proportion of truly favorable coordination opportunities that the model correctly identifies, defined as $\frac{\text{TP}}{\text{TP+FN}}$, which measures how well the model captures all feasible opportunities.
- Specificity: the proportion of truly unfavorable coordination attempts that the model correctly identifies as unfavorable, defined as $\frac{\text{TN}}{\text{TN+FP}}$, which measures the model's ability to avoid false positives among negative cases.

Together, these metrics provide a comprehensive assessment of prediction performance, reflecting both the model's capacity to correctly identify feasible coordination events and its ability to limit false positives.

Figures 3 and 4 summarize the performance of the proposed framework under different traffic densities, coordination avoidance ranges, prediction methods, and classification thresholds. In the plots, "BP" denotes the use of the baseline trajectory prediction, while "IP" refers to the ideal prediction. The labels "Conservative", "Moderate", and "Aggressive" indicate the three classification thresholds adopted by the AI module when assisting the deterministic algorithm, applied consistently to both BP and IP cases. For instance, "Conservative (BP)" means the AI model uses a conservative threshold and intent sharing data coming from baseline trajectory prediction. For completeness, Figure 3 also reports the performance of the deterministic algorithm alone, without AI support, labeled as "Algorithm (BP)" and "Algorithm (IP)". For these cases, only the success ratio is evaluated, as precision, recall, and specificity are not defined in the absence of the AI-based classification stage.

Figure 3 reports the success ratio values across all configurations: the deterministic algorithm without the integration of the AI module, and the complete framework under the three different classification thresholds. Success ratios improve substantially when moving from algorithm-only approaches to AI-assisted ones. In particular, the conservative and moderate classification thresholds perform well across both traffic densities (15 and 25 veh/km/lane) and coordination avoidance ranges (200 m and 500 m) when baseline prediction is used. Overall, the highest coordination success ratios are achieved when using a conservative classification threshold. A more conservative threshold reduces the likelihood of false positives, ensuring that only coordination maneuvers with a high predicted chance of success are executed.

Figure 4 summarizes the precision, recall, and specificity of the proposed framework under different classification thresholds. The highest precision is consistently achieved when ideal trajectory prediction is employed, regardless of traffic density or coordination avoidance range. In contrast, recall and specificity are the metrics most sensitive to the selected classification threshold and exhibit opposing trends: more aggressive thresholds increase recall while reducing specificity. This behavior reflects the well-known trade-off between proactive intervention and a higher incidence of false positives. Overall, these results demonstrate the benefit of integrating good trajectory representations of future vehicle behavior with AI-driven decision-making to improve maneuver coordination performance.

Notably, the framework exhibits a reduction in specificity when operating on the dataset that employs the ideal trajectory prediction, primarily due to the strong class imbalance inherent in the related dataset. In fact, the deterministic algorithm performs well when future trajectories are close to reality, as is the case with the ideal trajectory prediction, which provides the most accurate approximation of actual traffic conditions. This behavior is reflected in the success ratio results of the deterministic algorithm, presented in Figure 3. However, the class imbalance increases the tendency of the model to generate false positives. For this reason, specificity measured with baseline prediction (i.e., with a more balanced dataset) is generally higher, as the reduced dominance of positive samples limits false-positive generation and allows the classifier to better discriminate unsuccessful coordination events.

As expected, increasing traffic density naturally reduces success ratios for all methods. Higher vehicle densities lead to more frequent potential conflicts and make maneuver coordination more challenging. Nevertheless, the integration of the AI model mitigates this degradation relative to the deterministic algorithm, demonstrating improved robustness under congested conditions.

Extending the coordination avoidance range from 200 m to 500 m further enhances safety by providing a larger buffer for maneuver coordination. This adjustment improves both success ratios, precision, and recall across all scenarios.

In general, adopting a conservative threshold tends to maximize specificity, precision, and success ratio at the expense of recall, whereas moderate and aggressive thresholds favor higher recall, highlighting the inherent trade-offs among these performance metrics.

Overall, integrating the AI model with the deterministic algorithm enables robust and reliable lane change coordination. Even with simple trajectory predictions, the system leveraging the AI model can match or surpass the performance of the algorithm using ideal predictions by anticipating potential coordination failures.

V. Conclusions

Maneuver coordination among connected and autonomous vehicles remains a fundamental challenge for the development of reliable and efficient Intelligent Transportation Systems. This work presented a lane change maneuver coordination framework that augments a deterministic coordination algorithm with an AI-based decision module capable of filtering coordination requests that are likely to be unsuccessful under dynamic traffic conditions. Results across varying traffic densities, coordination avoidance ranges, classification thresholds, and trajectory prediction strategies, demonstrate that integrating the AI module consistently enhances coordination performance by explicitly capturing traffic dynamics and temporal variations that are challenging for deterministic algorithms to model. The analysis highlights the trade-off between conservative and more proactive strategies, with the choice ultimately depending on the system's intended level of intervention. Importantly, the proposed framework enables classical deterministic methodologies, typically sensitive to prediction inaccuracies caused by traffic variability as well as to complex traffic dynamics, to achieve reliable performance, thereby enhancing overall system robustness. Future work will extend this framework for integration into a V2X simulation to further evaluate its reliability and effectiveness in realistic cooperative driving scenarios.

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