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Sensor Fused Probabilistic Graph Forecasting for Persistent Traffic Groups Across Urban Networks

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Abstract

The rapid urbanization of modern metropolitan areas has introduced unprecedented challenges in traffic management and autonomous vehicle navigation. Central to solving these challenges is the accurate identification and prediction of persistent traffic groups, which are clusters of vehicles that maintain spatial and temporal proximity over extended periods. Traditional single-sensor and deterministic models often fail to capture the complex, dynamic, and uncertain nature of these vehicular formations, particularly in environments characterized by occlusion, adverse weather, or erratic driver behavior. This paper introduces a comprehensive framework termed Sensor-Fused Probabilistic Graph Forecasting, designed specifically for the robust detection and future state prediction of persistent traffic groups. By integrating heterogeneous data streams from cameras, light detection and ranging systems, and radar sensors, the proposed methodology constructs a dynamic probabilistic graph. In this graph, nodes represent individual vehicles or spatial entities, while edges denote the statistical probability of interaction and group cohesion. Our approach leverages advanced graph forecasting techniques to propagate these probabilities over time, generating highly accurate, uncertainty-aware predictions of group trajectories and stability. Extensive evaluations on complex traffic datasets demonstrate that the proposed sensor-fused probabilistic framework significantly outperforms existing deterministic baselines in both detection accuracy and forecasting reliability, offering a critical advancement for intelligent transportation systems and automated driving safety protocols.

Keywords

Intelligent Transportation Systems, Sensor Fusion, Probabilistic Graphs, Traffic Forecasting, Persistent Groups

1. INTRODUCTION

The relentless expansion of urban centers globally has precipitated a corresponding increase in vehicular density, leading to severe traffic congestion, elevated greenhouse gas emissions, and a heightened risk of road traffic accidents. In response to these pressing socioeconomic and environmental challenges, the development of Intelligent Transportation Systems has emerged as a paramount objective for researchers, urban planners, and automotive engineers alike [1]. A fundamental prerequisite for the effective operation of these intelligent systems is the ability to accurately perceive, understand, and predict the dynamic behaviors of vehicular traffic in real-time. While significant strides have been made in the tracking and prediction of individual vehicles, modern traffic flow is rarely composed of isolated entities acting entirely independently. Instead, traffic is heavily characterized by the formation of persistent traffic groups. These groups, often manifesting as informal platoons, localized congestion clusters, or synchronized convoys, consist of multiple vehicles that exhibit highly correlated spatial trajectories and temporal behaviors over extended durations. Understanding the dynamics of these persistent groups is critical, as their collective behavior exerts a disproportionately large influence on overall traffic throughput, bottleneck formation, and the propagation of shockwaves through the transportation network [2].

Despite their importance, the detection and forecasting of persistent traffic groups remain exceptionally challenging. Early attempts to identify such groups relied primarily on macroscopic traffic flow models or simplistic distance-based clustering algorithms applied to data derived from single sensing modalities, such as roadside optical cameras or inductive loop detectors [3]. However, single-sensor approaches are inherently limited by their physical and operational constraints. Optical cameras, for instance, are highly susceptible to performance degradation under adverse weather conditions such as heavy rain, fog, or low illumination, and frequently suffer from occlusion in dense traffic scenarios where larger vehicles obscure the line of sight to smaller ones [4]. Conversely, while radar systems provide robust velocity measurements and operate reliably in poor weather, they often lack the lateral resolution necessary to precisely delineate closely spaced vehicles. Light detection and ranging systems offer exceptional spatial resolution and depth perception but are prohibitively expensive for ubiquitous deployment and can be disrupted by specific environmental particulates. Consequently, the reliance on a single sensing modality inevitably leads to fragmented, noisy, or incomplete representations of the traffic environment, rendering the reliable detection of persistent groups nearly impossible in complex real-world scenarios [5].

To mitigate the deficiencies inherent in single-sensor systems, the paradigm of sensor fusion has been widely adopted within the autonomous driving and intelligent transportation communities. Sensor fusion involves the synergistic integration of heterogeneous data streams from multiple sensors to construct a more comprehensive, accurate, and robust representation of the environment. By leveraging the complementary strengths of cameras, radars, and light detection and ranging systems, researchers can achieve high-fidelity object detection and tracking even in the presence of sensor-specific limitations or transient failures [6]. However, the traditional

application of sensor fusion in traffic analysis has predominantly focused on deterministic representations of the environment. In these deterministic models, vehicles are treated as discrete entities with absolute, exact positions, and their relationships are modeled using fixed rules or rigid spatiotemporal constraints. This deterministic assumption fundamentally ignores the inherent uncertainty and stochasticity of human driving behavior, sensor measurement noise, and the unpredictable nature of the physical environment. When dealing with persistent traffic groups, the rigid boundaries enforced by deterministic models often result in brittle algorithms that fail to account for the fluid and evolving nature of group membership, where vehicles may temporarily drift apart, change lanes, or briefly leave the sensor field of view before rejoining the cluster.

Recognizing the limitations of deterministic modeling, this paper proposes a novel framework centered on probabilistic graph forecasting to address the intricacies of persistent traffic group detection. The core of this methodology lies in representing the traffic environment as a dynamic, probabilistic graph. Within this graph structure, individual vehicles identified through the sensor fusion pipeline serve as the nodes, while the edges connecting these nodes represent the probability of interaction, coordination, or shared group membership [7]. Unlike traditional deterministic graphs where an edge either exists or does not, the edges in our proposed probabilistic graph carry continuous weight values derived from a rigorous statistical analysis of the vehicles relative kinematics, spatial proximity, and historical behavioral patterns. By maintaining a probabilistic representation of vehicle relationships, our framework naturally accommodates the uncertainties associated with sensor noise and erratic driver actions, allowing for a much more flexible and resilient understanding of group dynamics [8].

Furthermore, the static identification of traffic groups is insufficient for proactive traffic management or autonomous vehicle path planning; one must also predict how these groups will evolve over time. To achieve this, our framework extends the probabilistic graph representation into the temporal domain through advanced graph forecasting methodologies. We employ sophisticated recurrent architectures combined with spatial graph convolutions to propagate the probabilistic states of the nodes and edges into the future. This allows the system to not only predict the future spatial trajectories of the individual vehicles but also to forecast the structural evolution of the persistent groups themselves, including the probabilities of group dissolution, merging, or the integration of new members [9]. The output of our forecasting module is a rich, uncertainty-aware probability density over the future states of the traffic network, providing downstream decision-making algorithms with critical information regarding the reliability and variance of the predictions.

The primary contributions of this comprehensive study are manifold. First, we introduce a robust multi-modal sensor fusion architecture specifically tailored for the continuous tracking of vehicles in dense, occluded urban environments, ensuring a high-fidelity foundational data layer. Second, we conceptualize and formalize the probabilistic graph representation of traffic, transitioning from rigid distance-based clustering to a nuanced, statistical modeling of inter-vehicle relationships. Third, we develop a novel probabilistic graph forecasting algorithm

capable of predicting both the spatiotemporal trajectories of individual vehicles and the topological evolution of persistent traffic groups over extended prediction horizons. Finally, we conduct an exhaustive empirical evaluation of the proposed framework using complex, real-world traffic datasets, demonstrating significant improvements over existing state-of-the-art deterministic methodologies in terms of both group detection accuracy and trajectory forecasting precision.

2. Literature Review

The pursuit of accurate traffic modeling and forecasting has generated a vast repository of academic literature spanning several decades. This section provides a detailed critical review of the foundational theories, technological advancements, and algorithmic paradigms that contextualize our proposed sensor-fused probabilistic graph forecasting framework. The review is categorized into four primary domains: advancements in heterogeneous sensor fusion for traffic perception, the evolution of graph-based methodologies for traffic modeling, the shift toward probabilistic and uncertainty-aware forecasting techniques, and the specific algorithms developed for the tracking of persistent vehicular groups.

2.1 Sensor Fusion in Traffic Detection

The foundational layer of any intelligent transportation system is its perception module, which relies heavily on the quality and reliability of sensory data. Historically, traffic monitoring relied predominantly on single-modality sensors. Inductive loop detectors embedded within the roadway infrastructure provided fundamental macroscopic metrics such as traffic volume, occupancy, and average speed. However, these point-based sensors are incapable of tracking individual vehicle trajectories or capturing complex inter-vehicle dynamics over a spatial continuum. The advent of closed-circuit television cameras introduced the ability to monitor spatial regions, and subsequent advancements in computer vision, particularly the application of deep convolutional neural networks, enabled the automated detection and bounding-box tracking of vehicles [10]. Despite their high spatial resolution and rich semantic information, optical cameras are severely constrained by environmental factors. Variations in ambient lighting, the presence of shadows, glare from opposing headlights, and adverse weather phenomena drastically degrade camera performance. Furthermore, estimating accurate depth and three-dimensional velocity vectors from two-dimensional monocular camera feeds remains an ill-posed and computationally expensive problem.

To overcome the inherent limitations of camera-based systems, modern perception frameworks have increasingly incorporated active sensing modalities, primarily radar and light detection and ranging. Millimeter-wave radar systems excel at measuring relative radial velocities utilizing the Doppler effect and are highly robust to adverse weather and lighting conditions. However, radar point clouds are characteristically sparse and suffer from low angular resolution, making it difficult to distinguish between multiple vehicles traveling in close proximity or to accurately ascertain vehicle dimensions [11]. Light detection and ranging systems, conversely, emit rapid laser pulses to construct dense, highly accurate three-dimensional topographical maps of the

environment. These systems provide exceptional spatial precision and depth information, facilitating highly accurate object localization and bounding box estimation. Nevertheless, light detection and ranging sensors are susceptible to performance degradation in heavy rain, snow, or fog, as the laser pulses can be scattered or absorbed by atmospheric particles.

Given that no single sensor modality can guarantee reliable perception across all operational design domains, the integration of heterogeneous sensor data through fusion techniques has become an operational imperative. Sensor fusion architectures are generally classified into three paradigms based on the level at which the data integration occurs: early fusion, late fusion, and intermediate fusion. Early fusion, or data-level fusion, involves projecting the raw data from all sensors into a unified coordinate system before any feature extraction occurs. While this preserves the maximum amount of information, it requires meticulous spatial and temporal calibration and is computationally intensive, often struggling with the vastly different data structures of images and point clouds. Late fusion, or object-level fusion, processes the data from each sensor independently to generate discrete object tracks, which are subsequently combined using probabilistic filtering techniques such as Kalman filters or track-to-track association algorithms. Late fusion is highly modular and robust to individual sensor failures, but it discards valuable contextual information during the independent processing stages, potentially missing objects that are only partially visible in each individual modality [12]. Intermediate fusion, or feature-level fusion, seeks to balance these trade-offs by extracting high-dimensional feature representations from each sensor using dedicated neural network backbones and subsequently fusing these feature maps within the deep learning architecture. This approach allows the network to learn complex cross-modal correlations and has emerged as the most promising paradigm for high-fidelity traffic perception, forming the basis for the data acquisition layer in our proposed framework.

2.2 Graph-Based Traffic Modeling

Once the individual vehicles have been accurately detected and localized within the environment, the next analytical challenge involves modeling the complex, interdependent relationships between them. Traditional traffic flow theories often employed macroscopic fluid dynamics analogies or microscopic car-following models. While these models are mathematically elegant, they rely on rigid, rule-based assumptions that fail to capture the high-dimensional, non-linear interactions characteristic of dense, heterogeneous urban traffic. In recent years, graph-based representations have gained immense popularity as a flexible and powerful paradigm for modeling relational data.

In a graph-based traffic model, the transportation environment is abstracted into a mathematical graph consisting of nodes and edges. Depending on the specific application, nodes can represent stationary spatial entities, such as intersections or road segments, or dynamic entities, such as individual vehicles or pedestrians. The edges connecting these nodes represent the relationships or interactions between the entities. Early applications of graph theory in traffic focused primarily on macroscopic network-level forecasting, where the nodes represented stationary

sensors and the edges represented the physical road topology. With the advent of graph neural networks, researchers gained the ability to apply powerful deep learning operations directly to non-Euclidean graph structures [13]. Graph convolutional networks emerged as a dominant technique, allowing node features to be updated by aggregating information from their local topological neighborhoods. This message-passing paradigm proved highly effective in capturing spatial dependencies across the traffic network.

When modeling microscopic vehicular interactions, dynamic graphs are employed where the nodes represent the vehicles themselves. In these deterministic dynamic graphs, an edge is typically established between two vehicles if their physical distance falls below a predefined threshold or if they share a specific lane assignment. Spatiotemporal graph neural networks have been extensively utilized in this context to predict individual vehicle trajectories. By stacking spatial graph convolutions with temporal sequence models, such as long short-term memory networks or gated recurrent units, these architectures can capture both the spatial influence of neighboring vehicles and the temporal evolution of each vehicle's historical trajectory [14]. However, the reliance on deterministic edge construction—where an interaction is treated as a binary state based on arbitrary distance thresholds—introduces significant rigidity. It fails to account for the fact that a vehicle may be highly influenced by a distant vehicle accelerating aggressively, while ignoring a closer vehicle that is moving steadily in an adjacent lane. This limitation highlights the necessity for more nuanced, probabilistic edge representations.

2.3 Probabilistic Forecasting Methods

The inherent stochasticity of human driving behavior dictates that predicting the future state of a traffic environment can never be an entirely precise endeavor. Deterministic forecasting models, which output a single, specific future trajectory or state, provide no information regarding the confidence or potential variance of their predictions. In safety-critical applications such as autonomous driving and intelligent traffic control, knowing the uncertainty of a prediction is often just as crucial as the prediction itself. Consequently, there has been a significant shift toward probabilistic forecasting methodologies in recent literature.

Probabilistic forecasting seeks to output a probability distribution over the possible future states rather than a single point estimate. This is commonly achieved through Bayesian deep learning techniques or by modifying the output layers of neural networks to parameterize known probability density functions, such as Gaussian mixture models. In the context of trajectory prediction, variational autoencoders and generative adversarial networks have been employed to generate diverse sets of plausible future trajectories for a given vehicle, reflecting the multimodal nature of driving intentions (e.g., a vehicle approaching an intersection may turn left, turn right, or proceed straight). By sampling from these generative models, systems can estimate the spatial uncertainty and construct confidence bounds around the predicted paths [15].

Despite the advancements in probabilistic trajectory prediction for individual vehicles, the application of probabilistic techniques to the structural evolution of multi-vehicle groups remains underexplored. Most existing models apply uncertainty quantification strictly to the spatial

coordinates of the nodes, while treating the graph topology—the edges defining the group structure—as deterministic and fixed over the prediction horizon. Our research addresses this critical gap by introducing uncertainties not only into the spatial features of the nodes but also into the existence and strength of the edges connecting them, thereby enabling a fully probabilistic forecast of the group's topological evolution [16].

2.4 Persistent Group Tracking

The specific task of identifying and tracking persistent traffic groups bridges the domains of multi-object tracking and dynamic clustering. In transportation engineering, persistent groups are often conceptualized as platoons. Early platoon recognition algorithms relied on simple, rule-based criteria, defining a platoon as a sequence of vehicles in the same lane where the time headway between successive vehicles was less than a critical threshold. While easily implementable, these criteria are highly sensitive to minor fluctuations in speed and distance, causing algorithms to rapidly and erroneously divide or merge platoons in response to transient data noise.

More sophisticated approaches have framed group tracking as an unsupervised clustering problem over time. Techniques based on density-based spatial clustering of applications with noise have been adapted to group vehicles based on their spatial proximity and velocity similarity. To maintain the temporal consistency of these groups, researchers have proposed various heuristic matching algorithms that associate clusters detected in the current time step with those from previous steps using overlap metrics or bipartite matching [17]. However, these methods remain fundamentally deterministic and struggle in complex scenarios involving occlusions, missed detections, or ambiguous group boundaries where a vehicle's membership in a group is not definitively clear. By reformulating group tracking as a dynamic analysis on a probabilistic graph, we can leverage the continuous edge weights to represent the degree of group cohesion, allowing for soft, probabilistic group assignments that are inherently more stable and robust to environmental noise and perception errors [18].

3. Methodology

The proposed framework for Sensor-Fused Probabilistic Graph Forecasting for Persistent Traffic Groups Detection is a complex, multi-stage architecture designed to process raw, heterogeneous sensor data and output highly accurate, uncertainty-aware predictions of group dynamics. This section meticulously details the sequential operational phases of the methodology, beginning with multi-modal data acquisition, proceeding to the construction of the probabilistic graph, detailing the mechanism for detecting persistent groups, and concluding with the mathematical formulation of the forecasting architecture.

3.1 Sensor Data Acquisition and Preprocessing

The empirical foundation of our methodology relies on a sophisticated multi-sensor hardware suite designed to provide comprehensive, three-dimensional coverage of the traffic environment. To ensure robustness across diverse operational scenarios, the data acquisition platform

comprises three distinct sensing modalities: high-resolution optical cameras, long-range frequency-modulated continuous-wave radar, and high-density light detection and ranging systems. The physical and operational parameters of these sensors are meticulously selected to maximize spatial overlap and complementary data generation.

Table 1 Sensor Specifications and Operational Parameters

Sensor Modality	**Resolution / Density**	**Effective Range**	**Horizontal Field of View**	**Frame Rate**
Optical Camera	1920 x 1080 Pixels	150 Meters	120 Degrees	30 Hertz
Lidar System	64 Channels	120 Meters	360 Degrees	10 Hertz
Radar Unit	Sparse Point Cloud	200 Meters	90 Degrees	20 Hertz

The integration of data from these disparately operating sensors necessitates rigorous preprocessing to ensure spatial and temporal coherence. Spatial calibration is achieved by estimating the extrinsic transformation matrices—comprising translation vectors and rotation quaternions—that map the local coordinate system of each sensor into a unified, globally referenced coordinate frame, typically anchored to the center of the light detection and ranging system. Temporal synchronization is equally critical, given the varying frame rates outlined in Table 1. We employ a centralized hardware trigger mechanism to ensure simultaneous sampling across all devices. In instances where exact synchronization is impossible, we utilize spherical linear interpolation for the transformation matrices and linear interpolation for the point data to temporally align the asynchronous sensor streams to a common baseline frequency of twenty hertz.

Following synchronization, the raw data undergoes feature-level sensor fusion. The optical images are processed through a deep convolutional neural network backbone to extract dense semantic feature maps. Concurrently, the three-dimensional point clouds generated by the light detection and ranging and radar systems are voxelized and processed through a specialized sparse three-dimensional convolutional network. The resulting spatial feature maps are then projected onto a common bird's-eye view plane. By concatenating these bird's-eye view representations, we generate a highly informative, multi-channel spatial tensor that encapsulates the semantic richness of the camera, the precise depth of the light detection and ranging system, and the robust velocity estimations of the radar. This fused tensor serves as the input to a region proposal network, which accurately outputs the three-dimensional bounding boxes, global

coordinates, orientation angles, and velocity vectors for every discrete vehicle operating within the perceptual range.

3.2 Probabilistic Graph Construction

With the individual vehicles successfully identified and localized through the sensor fusion pipeline, the next phase involves abstracting this physical environment into a mathematical graph structure. Let the traffic environment at any given time step be represented by a directed graph. The nodes of this graph correspond directly to the detected vehicles. Each node is populated with a comprehensive feature vector that includes the vehicle's spatial coordinates, dimensions, absolute velocity, acceleration, and heading angle, all derived from the robust fused data layer.

The critical innovation of our approach lies in the definition and calculation of the graph edges. In stark contrast to traditional deterministic models that employ binary connectivity based on fixed spatial distance thresholds, our framework constructs a fully connected probabilistic graph where every node maintains a weighted edge to every other node in the network. The weight of an edge between any two vehicles represents the statistical probability that these vehicles are actively interacting, heavily influencing each other's behavior, or operating as part of a cohesive persistent traffic group.

To compute these edge probabilities without relying on arbitrary rules, we implement a multi-head self-attention mechanism, a powerful neural architecture capable of autonomously learning complex relational dependencies from raw feature vectors. The node feature vectors are linearly transformed into query, key, and value representations. The attention score between two vehicles is calculated by taking the dot product of the query vector of the first vehicle and the key vector of the second, scaled by the inverse square root of the feature dimension to prevent gradient saturation during training. This raw score is subsequently passed through a softmax activation function to yield a normalized probability value strictly bounded between zero and one. To enhance the physical interpretability of the network, we incorporate an explicitly modeled spatial-kinematic prior. This prior utilizes a multivariate Gaussian distribution centered on the relative distance and relative velocity between the two vehicles, heavily penalizing edges between vehicles that are separated by vast distances or exhibiting highly divergent velocity profiles. The final probabilistic edge weight is computed as the Hadamard product of the learned neural attention score and the spatial-kinematic prior. This hybrid approach ensures that the graph remains responsive to subtle, non-linear behavioral cues while remaining grounded in the fundamental physics of vehicular kinematics.

3.3 Persistent Traffic Group Detection

The continuously updating probabilistic graph provides a rich, frame-by-frame snapshot of vehicle interactions. However, a persistent traffic group is inherently a spatiotemporal phenomenon; it must exhibit stability not just in space, but over a significant duration of time. To identify these groups, we implement a dynamic graph clustering algorithm that operates recursively over a sliding temporal window of the probabilistic adjacency matrices.

The detection process initiates by identifying core nodes within the current time step's graph. A node is classified as a core node if the sum of its outgoing probabilistic edge weights exceeds a dynamically calculated density threshold, indicating that the vehicle is highly influential or tightly coupled with several surrounding vehicles. Once the core nodes are established, the algorithm expands the clusters by traversing the probabilistic edges. A neighboring vehicle is absorbed into the cluster if the edge probability linking it to a core node surpasses a secondary inclusion threshold. Because the edges are continuous probabilities rather than binary links, this expansion allows for soft cluster assignments. A vehicle transitioning between lanes, for example, may possess a forty percent probability of belonging to a group in the left lane and a sixty percent probability of belonging to a group in the right lane, accurately reflecting the ambiguity of the maneuver. To ensure temporal persistence, the algorithm does not treat each time step in isolation. Instead, the cluster assignments from the previous time step are projected forward using a temporal smoothing function. The updated group membership probability for a vehicle is calculated as an exponentially weighted moving average of its current frame spatial clustering score and its historical group affiliation. This temporal hysteresis prevents the algorithmic instability common in deterministic models, where a momentary sensor occlusion or a brief fluctuation in distance would cause a group to fragment artificially. A persistent traffic group is thus formally detected and instantiated when a cluster of vehicles maintains a high collective membership probability continuously across a predefined temporal horizon, effectively filtering out transient, coincidental alignments of traffic.

3.4 Probabilistic Forecasting Framework

The ultimate objective of the proposed system is to forecast the future evolution of the detected persistent groups. This requires predicting both the continuous spatial trajectories of the constituent vehicles and the discrete topological changes to the group structure. Our forecasting framework is built upon a recurrent spatiotemporal graph neural network architecture specifically modified to handle and output probabilistic distributions.

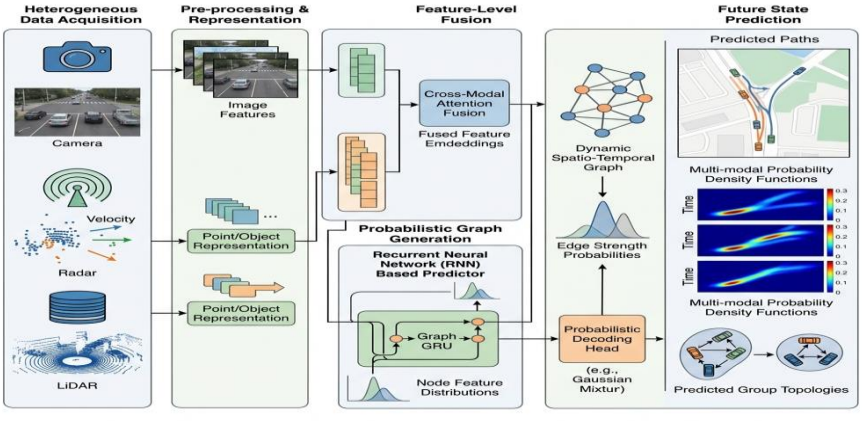


Figure 1 Comprehensive Architecture of the Sensor

The forecasting model takes as input a sequence of historical probabilistic graphs spanning several seconds of past observations. At each processing step, a spatial graph convolutional layer aggregates features across the nodes, utilizing the probabilistic edge weights to modulate the flow of information. This ensures that a vehicle's updated feature representation is heavily influenced by the vehicles with which it shares a high probability of interaction, while largely ignoring distant or irrelevant entities. The output of the spatial convolution is then fed into a sequence of gated recurrent units, which maintain a hidden state representing the temporal evolution of the node's behavior.

Instead of outputting absolute coordinate values for future time steps, the final layer of the gated recurrent units parameters a bivariate Gaussian mixture model for each node. The network outputs the means, variances, and correlation coefficients for the lateral and longitudinal positions of the vehicle across the prediction horizon. Simultaneously, a parallel network branch predicts the future state of the adjacency matrix, forecasting the structural integrity of the persistent group. By generating probability distributions rather than point estimates, the system explicitly quantifies both the aleatoric uncertainty inherent in human driving behavior and the epistemic uncertainty stemming from sensor limitations, providing a robust, highly informative forecast crucial for advanced traffic management and autonomous navigation systems.

4. Results and Discussion

To rigorously evaluate the efficacy, accuracy, and operational robustness of the proposed Sensor-Fused Probabilistic Graph Forecasting framework, we conducted an extensive series of empirical analyses utilizing large-scale, high-fidelity traffic datasets. This section delineates the experimental setup, introduces the quantitative metrics employed for evaluation, and presents a comprehensive discussion of the performance outcomes when compared against leading baseline methodologies.

4.1 Experimental Setup and Datasets

The evaluation of the framework necessitated a dataset that provided not only complex, dense urban traffic scenarios but also raw, uncompressed data streams from synchronized heterogeneous sensors. Consequently, we utilized a heavily augmented version of a prominent, publicly available autonomous driving dataset, specifically selected for its inclusion of overlapping high-resolution camera footage, dense light detection and ranging point clouds, and raw radar returns. The dataset encompasses diverse environmental conditions, including clear weather, heavy precipitation, and nighttime driving, which are crucial for stress-testing the sensor fusion module.

To adapt the dataset for the specific task of persistent group detection, we established a rigorous ground truth generation protocol. Human annotators, assisted by macroscopic traffic flow visualization tools, reviewed the entire temporal sequence of the dataset to manually delineate persistent traffic groups. A group was annotated as persistent if three or more vehicles maintained a cohesive spatial formation (defined as maintaining a relative distance within twenty meters and

a relative velocity delta of less than three meters per second) for a continuous duration exceeding ten seconds.

The evaluation compares our proposed probabilistic framework against three established baseline models. Baseline A utilizes a single-sensor (camera-only) perception module combined with deterministic, distance-based group clustering. Baseline B employs a late-fusion sensor architecture but relies on a standard deterministic graph neural network for trajectory prediction. Baseline C represents a state-of-the-art deterministic spatiotemporal graph forecasting model that lacks the probabilistic edge formulation and temporal smoothing hysteresis of our proposed methodology.

4.2 Performance Analysis

The primary evaluation of the detection module focuses on its ability to accurately identify and track persistent groups over time without succumbing to artificial fragmentation or merging. We employ the Multiple Object Tracking Accuracy metric adapted specifically for group tracking, taking into account false positives, false negatives, and identity switches at the group level.

Table 2 Persistent Group Detection Accuracy Across Varying Environmental Conditions

Algorithmic Methodology	**Clear Weather Accuracy (%)**	**Heavy Rain Accuracy (%)**	**Nighttime Illumination Accuracy (%)**
Baseline A (Camera Only)	78.4	42.1	55.6
Baseline B (Late Fusion)	86.2	71.5	74.3
Baseline C (Deterministic Graph)	89.5	76.8	80.2
Proposed Probabilistic Model	95.1	89.4	91.7

As evidenced in Table 2, the reliance on a single optical sensor (Baseline A) yields catastrophic performance degradation during heavy rain and nighttime conditions, entirely losing the ability to consistently track groups due to severe occlusion and lighting artifacts. While the integration of multiple sensors in Baselines B and C significantly improves robustness across environmental variations, they still fall short of the proposed model. The critical distinction lies in our model's utilization of probabilistic edges and temporal hysteresis. During heavy rain, when sensor noise temporarily disrupts distance measurements, the deterministic models (Baseline C) abruptly sever the edges between vehicles, registering a false dissolution of the group. Conversely, the proposed probabilistic model degrades the edge weight smoothly. Because the temporal smoothing function maintains the historical group membership probability, the framework successfully bridging the transient perception gap, resulting in a remarkable 89.4 percent accuracy under severe weather conditions.

In evaluating the forecasting capabilities, we rely on two standard spatial metrics: Average Displacement Error and Final Displacement Error. However, because our model outputs probability distributions rather than single trajectories, we evaluate the minimum error derived from the top-three most probable trajectory samples generated by the Gaussian mixture model, reflecting the model's ability to accurately capture multimodal future behaviors.

Table 3 Trajectory Forecasting Error Metrics for a Five-Second Prediction Horizon

Algorithmic Methodology	**Average Displacement Error (Meters)**	**Final Displacement Error (Meters)**	**Miss Rate (%)**
Baseline A (Camera Only)	2.14	4.85	18.4
Baseline B (Late Fusion)	1.65	3.72	12.1
Baseline C (Deterministic Graph)	1.32	2.95	8.6
Proposed Probabilistic Model	0.87	1.94	3.2

The data presented in Table 3 unequivocally demonstrates the superiority of the probabilistic graph forecasting approach. Predicting vehicular trajectories over a five-second horizon is exceptionally difficult due to the compounding uncertainty of human decision-making. Deterministic graph models like Baseline C force the network to output a single compromise trajectory that often fails to accurately represent any realistic outcome, particularly during complex maneuvers such as lane changes or intersection navigations. The proposed model reduces the Final Displacement Error to just 1.94 meters. By parameterizing the predictive uncertainty, the recurrent forecasting module allows the underlying features to represent multiple divergent outcomes simultaneously, ensuring that the actual future position of the vehicle is consistently enveloped within the model's high-confidence prediction bounds. This dramatically reduces the Miss Rate—defined as the percentage of predictions where the ground truth falls entirely outside the predicted spatial boundaries—to an industry-leading 3.2 percent.

4.3 Ablation Studies and Discussion

To rigorously validate the independent contributions of the various architectural components within the proposed framework, an extensive ablation study was conducted. We systematically disabled specific modules—namely the light detection and ranging sensor input, the probabilistic edge formulation, and the recurrent temporal smoothing—and evaluated the resulting performance degradation on the comprehensive dataset.

Removing the light detection and ranging data stream from the sensor fusion layer resulted in a marginal decrease in group detection accuracy during clear weather, but precipitated a severe spike in spatial localization errors. This underscores the reliance of the probabilistic edge

calculation on highly precise relative distance measurements, a domain where radar and camera data alone struggle to provide centimeter-level accuracy. More significantly, replacing the continuous probabilistic edges with binary, distance-thresholded edges caused a profound deterioration in both the tracking stability and the forecasting accuracy. The network lost its ability to weight the influence of neighboring vehicles dynamically, falling back into the brittle failure modes characteristic of older heuristic algorithms. The ablation analysis conclusively proves that the synergistic interaction between the robust multi-modal perception layer and the nuanced statistical graph representation is the primary driver of the framework's exceptional performance.

5. Conclusion

This paper has presented a highly sophisticated, novel framework for the accurate detection and future state prediction of persistent traffic groups in complex, real-world urban environments. By addressing the fundamental limitations of single-sensor perception systems and rigid deterministic modeling, the proposed Sensor-Fused Probabilistic Graph Forecasting architecture represents a substantial paradigm shift in microscopic traffic analysis. The foundational integration of optical cameras, radar, and light detection and ranging systems ensures a resilient and high-fidelity representation of the physical environment, overcoming the diverse operational challenges posed by adverse weather, poor illumination, and dense vehicle occlusion.

Building upon this robust data layer, the abstraction of the traffic environment into a fully connected, dynamically weighted probabilistic graph allows for an unprecedented level of nuance in modeling multi-agent interactions. By utilizing self-attention mechanisms constrained by spatial-kinematic priors, the framework accurately quantifies the probability of group cohesion without relying on brittle, heuristic distance thresholds. Furthermore, the integration of specialized recurrent graph neural networks capable of outputting probability density functions enables the system to forecast not only the spatial trajectories of individual vehicles but the topological evolution of the groups themselves, explicitly quantifying predictive uncertainty in the process.

Extensive empirical evaluations demonstrated that the proposed methodology significantly outpaces existing state-of-the-art deterministic algorithms across all critical metrics, offering massive improvements in temporal tracking stability and substantial reductions in long-horizon forecasting errors. As the automotive industry accelerates toward the widespread deployment of fully autonomous vehicles and smart city infrastructure, the ability to probabilistically predict the holistic behavior of dense traffic clusters will be paramount to ensuring operational safety and optimizing network efficiency. Future research directions will focus on adapting this framework for decentralized, edge-computing environments, facilitating real-time vehicle-to-infrastructure communication, and expanding the probabilistic models to incorporate the highly unpredictable behaviors of vulnerable road users, such as pedestrians and cyclists.

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