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# Ontology-Assisted Dynamic Spatiotemporal Feature Extraction for Short-Term Traffic Forecasting

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## ABSTRACT

Short-term traffic flow prediction is essential for intelligent transportation systems, enabling signal control, route planning, and congestion mitigation. However, existing methods often overlook flow fluctuations and underutilize temporal positional information, limiting spatiotemporal modeling performance. Therefore, this study proposed a dynamic spatiotemporal feature extraction (DSTFE) model that integrated temporal information and fluctuation features (TIFF) for enhanced traffic prediction—DSTFE-TIFF. Specifically, DSTFE-TIFF employed trigonometric time encoding to capture multiscale patterns and an exponentially weighted sliding window to emphasize recent, abrupt changes. These features were then integrated through a time-weighted attention framework, which modeled both local and long-range dependencies to form comprehensive spatiotemporal representations. Experiments on three data sets—the traffic-speed data set in the Los Angeles County road network, traffic-flow data set in the San Francisco Bay area, and traffic-flow data set in California—showed that DSTFE-TIFF achieved state-of-the-art performance, reducing key error metrics (mean absolute error, root mean square error, mean absolute percentage error) by over 22% on average versus baselines, demonstrating its effectiveness and robustness.

## KEYWORDS

Short-Term Traffic Flow Prediction, Sliding Window, Temporal Position Encoding, Dynamic Relational Module, Spatiotemporal Attention Fusion

## INTRODUCTION

In intelligent transportation systems, short-term traffic flow forecasting is a fundamental task that plays a vital role in alleviating congestion and optimizing route planning (Liang & Zhang, 2025). However, due to the inherent complexity and uncertainty of traffic systems, achieving high-precision prediction remains challenging. Specifically, traffic flow is influenced by both spatial structures and temporal patterns, exhibiting strong time dependencies, periodicity, and nonstationarity, often accompanied by abrupt local fluctuations under external disturbances.

In recent years, deep learning has been widely applied to traffic forecasting and has achieved significant progress in modeling complex spatiotemporal dependencies. For temporal modeling,

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recurrent neural networks (RNNs) and their variants, such as long short-term memory (LSTM) and gated recurrent units (Chauhan & Kumar, 2024; D. Li et al., 2025; Lu et al., 2021; Ma et al., 2024), have shown strong capabilities in capturing sequential dependencies. However, they still suffer from gradient degradation in long-term modeling. The transformer architecture, which introduces self-attention mechanisms, has emerged as a dominant approach for capturing long-range dependencies. However, transformer-based methods (Cheng et al., 2024; Jiang et al., 2023; Liu et al., 2023; Xing et al., 2024) tend to emphasize global dependencies while lacking sensitivity to short-term local variations. As a result, they often fail to effectively respond to nonstationary changes caused by sudden events, reducing their robustness in dynamic scenarios.

For spatial dependency modeling, early studies (Mourad et al., 2019; J. Zhang et al., 2017) typically converted traffic data into regular grids and applied convolutional neural networks (CNNs) to extract spatial features. While CNNs are effective in some scenarios, they are inherently designed for Euclidean structures. As a result, they struggle to represent irregular road networks, with grid partitioning often leading to a loss of spatial topology. To address this limitation, researchers have turned to graph neural networks (GNNs) to enhance modeling of non-Euclidean spatial data. Several studies (D. Bai et al., 2023; Y. Li et al., 2017; Song et al., 2020; Yu et al., 2017; Zhao et al., 2021) used adjacency or distance matrices to construct static graphs that capture spatial dependencies between nodes. Building on this idea, Bai et al. (2020) and Wu et al. (2020) introduced dynamic graph representations, allowing node embeddings to be updated during training and further enhancing model adaptability. Additionally, the model proposed by Chen et al. (2025) introduced independent and shared graph convolution modules to capture both intralayer variations and interlayer stability, enhancing spatial generalization capability.

Despite these advances, current methods still face three major limitations in complex and dynamic traffic environments. First, most models cannot jointly capture multiscale temporal structures, making it difficult to learn both long-term periodic trends and short-term local variations. Second, few methods incorporate dedicated mechanisms to model nonstationary fluctuations in traffic flow, resulting in reduced sensitivity to sudden disturbances. Third, spatial dependencies are often modeled solely based on geographic proximity, overlooking latent semantic correlations between distant nodes that share similar functional roles or traffic behaviors, which cannot be adequately represented by fixed topological structures.

To address these challenges, this study proposed a dynamic spatiotemporal feature extraction (DSTFE) model that integrated temporal information and fluctuation features (TIFF) for enhanced traffic prediction—DSTFE-TIFF. The model encoded temporal positions using trigonometric functions to capture multiscale periodic patterns (minutes, hours, days) and improve temporal dependency modeling. To characterize nonstationary fluctuations, an exponentially decaying weighted strategy was applied within a sliding window, emphasizing recent variations while highlighting abrupt changes. These temporal and fluctuation features were then fused through a dynamic relational modeling module with a hybrid attention mechanism, enabling adaptive feature interaction. Furthermore, a spatiotemporal attention fusion module jointly modeled temporal and spatial dependencies, while an adaptive fusion method optimized the integration of both aspects. Experiments on the traffic-flow data set in the San Francisco Bay area (PeMSD4), traffic-flow data set in California (PeMSD8), and traffic-speed data set in the Los Angeles County road network (METR-LA) demonstrated that DSTFE-TIFF achieved superior performance in root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). These results confirmed its effectiveness in integrating temporal information and fluctuation-aware modeling. The contributions of this paper are:

1. We proposed a multi-scale temporal position encoding method and fluctuation modeling mechanism, which jointly encoded periodic temporal structures and local nonstationary variations, providing a unified framework for modeling complex temporal dependencies.