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Ph.D. DISSERTATION DEFENSE

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Title:	Enhancing Urban Traffic Monitoring: Methods for Anomaly Detection and Data Imputation
Chairperson:	Dr. Mohammad Ilbeigi, Department of Civil, Environmental and Ocean Engineering, School of Engineering & Sciences
Committee Members:	Dr. George Korfiatis, Department of Civil, Environmental and Ocean Engineering, Stevens Institute of Technology Dr. Kaijian Liu, Department of Civil, Environmental and Ocean Engineering, Stevens Institute of Technology Dr. Mostafa Reisi Gahrooei, Department of Industrial and Systems Engineering, University of Florida

ABSTRACT

In today's rapidly growing urban environments, ensuring the resilience and efficiency of traffic systems is crucial not only for smooth daily mobility but also for effective responses during extreme events. Disruptions caused by natural disasters, large-scale incidents, and localized events can lead to significant congestion and severely affect emergency response operations. Consequently, timely and reliable detection of such disruptions is vital for effective traffic management. This dissertation introduces innovative methodologies aimed at enhancing traffic monitoring and anomaly detection in urban networks during these events, along with a targeted approach to improving the timely detection of incidents on freeways.

First, a novel PARATUCK2 data imputation method is introduced to reliably estimate missing data in large traffic networks by capturing the clustered spatiotemporal dynamics inherent in traffic flows. Second, a temporal self-expressive network monitoring method is proposed for detecting both large-scale and localized traffic anomalies during extreme events. This dual-level detection approach enables traffic authorities to evaluate the overall status of the traffic network while identifying the most affected areas that require immediate attention. Third, a Self-Imputing Deep Multitask Sequence (SI-DMSeq) model is presented, which integrates data imputation with anomaly detection tasks to enhance the efficiency of traffic monitoring in complex urban environments. Lastly, a Cycle-Consistent Bidirectional Graph Generative Adversarial Network (CCB-GraphGAN) is introduced to improve lane-level anomaly detection in freeway systems, aiming to enhance both the accuracy and timeliness of incident detection.

The proposed methodologies are evaluated using real-world traffic datasets, such as the New York City traffic dataset and the Interstate 24 traffic dataset. These evaluations demonstrate significant improvements in traffic monitoring and anomaly detection and underscore the practical applicability of these methods in real-world scenarios. By effectively addressing data gaps and improving timely anomaly detection, this research

contributes to the development of more resilient and adaptive transportation networks that are better equipped to serve both routine traffic and the demands of extreme events.