CICTP 2025

华南理工大学
South China University of Technology

The 25th COTA International Conference of Transportation Professionals

Transportation • Artificial Intelligence (AI) • Energy

July 22nd – 25th, 2025 Guangzhou, China

Adaptive Truncated Schatten Norm for Traffic Data Imputation with Complex Missing Patterns

*Haopeng Deng, Fucheng Zheng, Kaixiang Ma, Xinhai Xia**

School of Future Transportation, Guangzhou Maritime University

Introduction & Contributions

As urban traffic systems expand in scale and complexity, factors such as sensor malfunctions and communication interruptions intertwine, resulting in **complex and variable data missing patterns** (See *Fig. 1*). This severely threatens the reliability of Intelligent Transportation Systems (ITS) decisions [1]. Traditional temporal, spatial, and certain spatiotemporal data imputation methods often struggle to simultaneously achieve both accuracy and efficiency when dealing with complex missing patterns involve multiple causes. To address these limitations, we propose the **LRTC-ATSN** model. Our contributions are as follows:

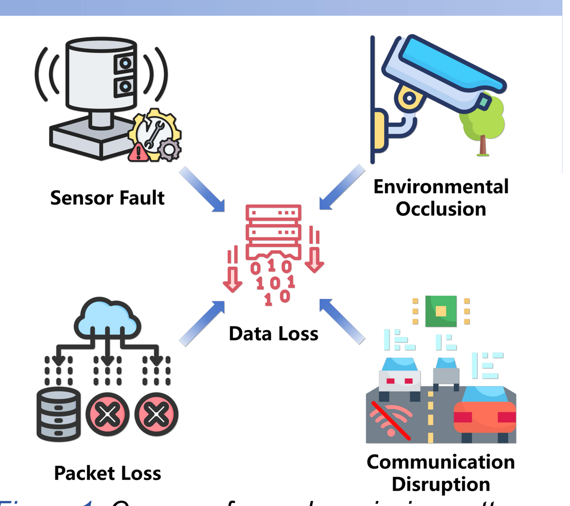

Figure 1. Causes of complex missing patterns

1. **Mixed Missing Pattern Generator:** To simulate element-wise, fiber-wise, and mixed data loss, providing a standardized testbed for robust algorithm evaluation.
2. **Design of the LRTC-ATSN Model:** Based on the adaptive truncation of the Schatten norm, effectively improving completion accuracy in complex missing scenarios.
3. **Integrated Optimization Strategy:** Employed the Adan optimizer with Nesterov momentum, leading to accelerated model convergence and robust performance on large-scale data.

Methodology

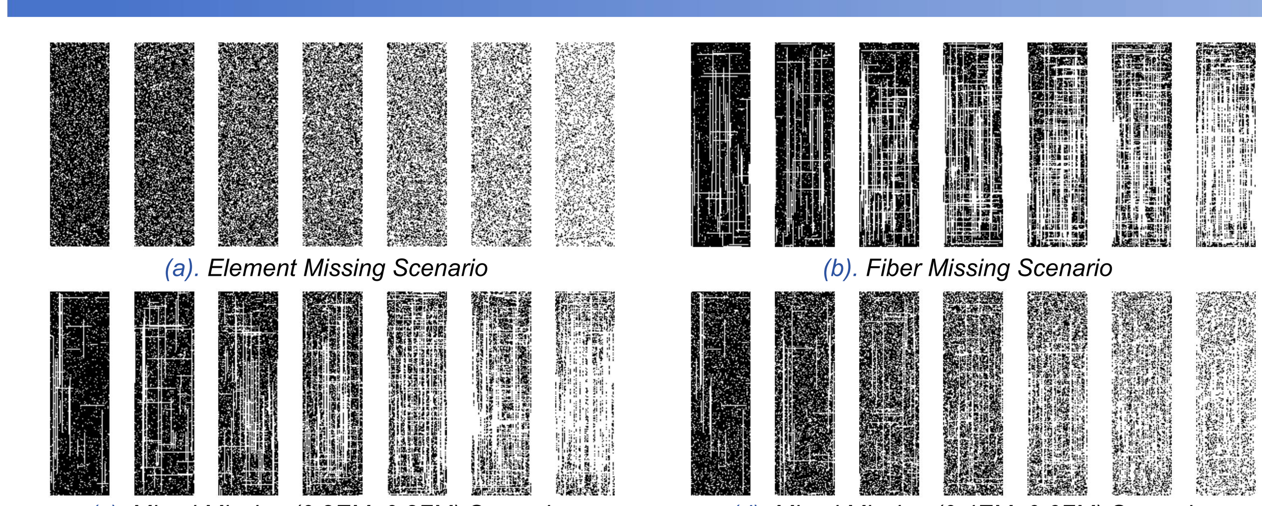

Figure 2. Traffic Flow Tensor slice variations across various missing patterns, 20~80% missing rates

I. Mixed Missing Pattern Generator

Our generator precisely reconstructs real-world missing characteristics by: simulating **Element Missing (EM)**, which depicts sporadic data point lossess due to sensor malfunctions or transient transmission errors; modeling **Fiber Missing (FM)**, representing prolonged data outages along specific dimensions caused by system failures; and creating **Mixed Missing (MM)**, synthesizing complex scenarios by combining EM and FM, with proportions informed by historical traffic data.

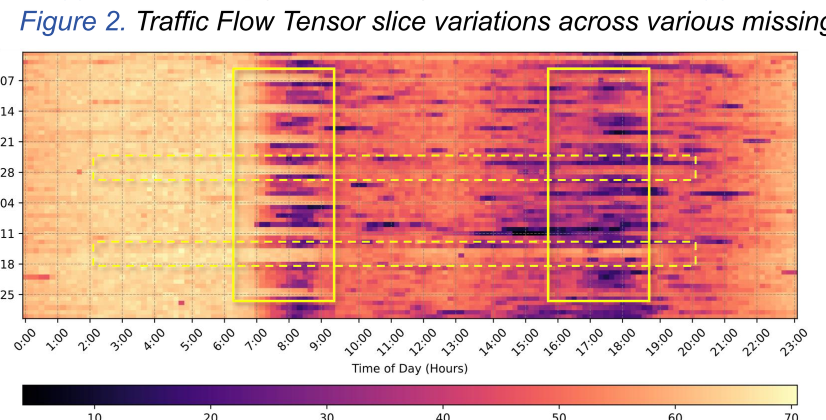

Figure 3. Slice Features of the Guangzhou Traffic Speed Tensor

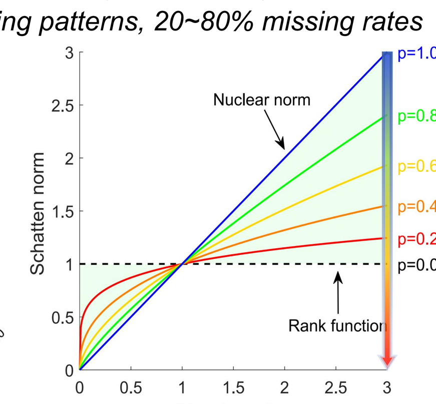

Figure 4. Schatten Norm Curve

II. Design of the LRTC-ATSN Model

Traffic data exhibits **spatiotemporal correlations** (*Fig. 3*), forming a low-rank structure, which we leverage for missing data recovery. Unlike traditional nuclear norm-based **Low-Rank Tensor Completion (LRTC)** methods with fixed truncation thresholds and mode weights [2][3], we introduce a flexible **Schatten norm-based** low-rank approximation (*Fig. 4*). Crucially, our **adaptive update mechanism** dynamically adjusts exponential parameters p, truncation rate θ, and mode weights α_k across different datasets, missing patterns, and iteration stages, thereby achieving an optimal balance between solution precision and computational efficiency.

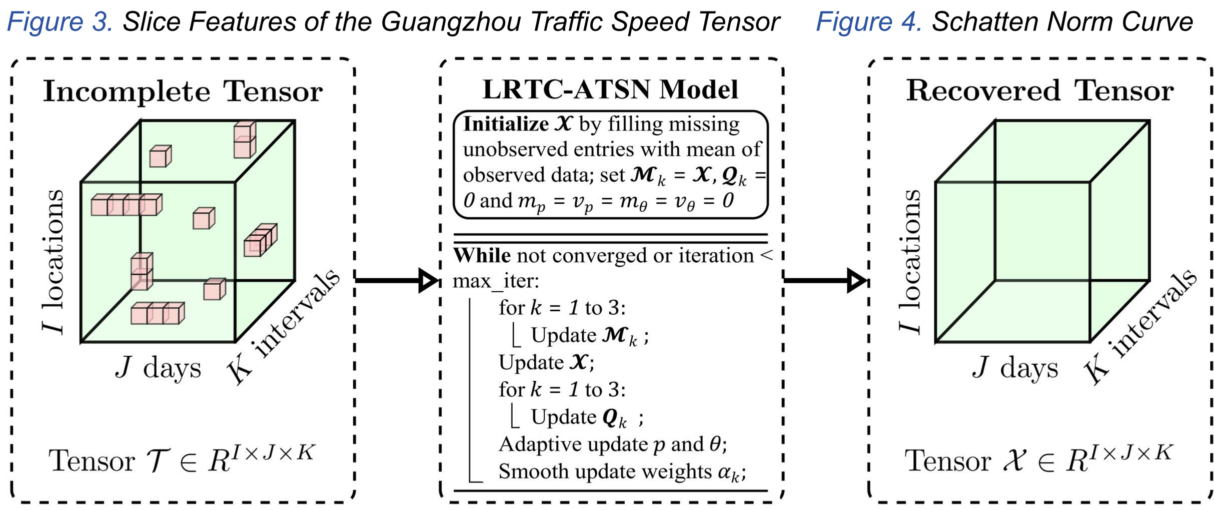

Figure 5. Solution Framework of the LRTC-ATSN Model

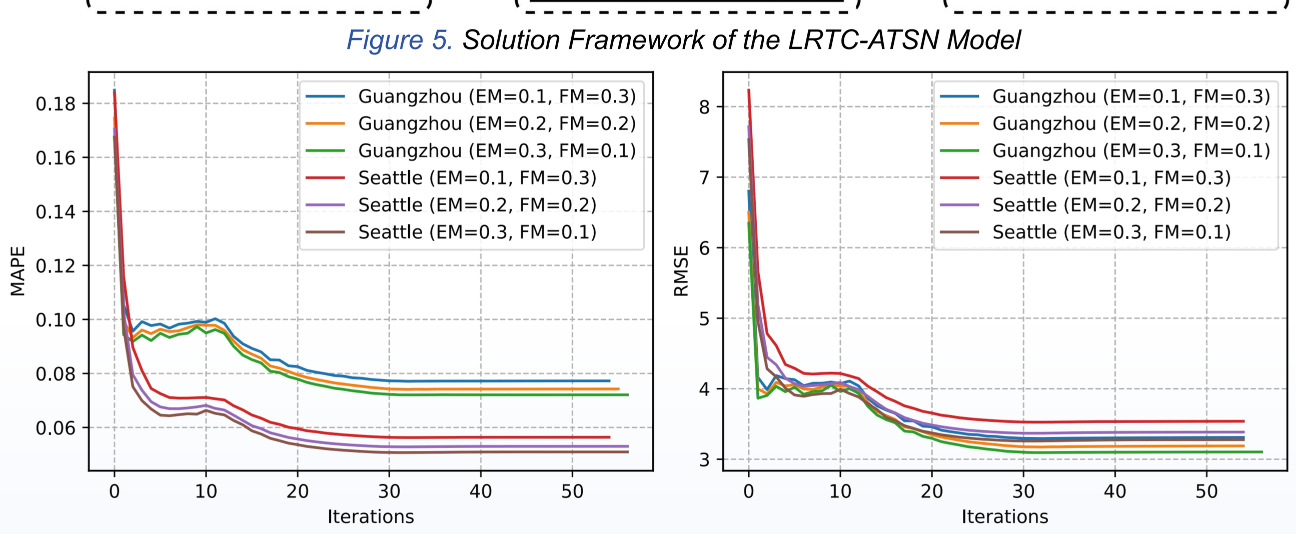

Figure 6. Convergence Performance of the LRTC-ATSN Model under Different Scenarios

III. Integrated Optimization Strategy

To effectively solve this non-convex optimization problem, we developed the **ADMM-TGST** (Alternating Direction Method of Multipliers with Truncated Generalized Soft Thresholding) framework (*Fig. 5*), which decomposes the problem into simpler, solvable subproblems . By integrating the **Adan algorithm** with Nesterov momentum for iterative parameter optimization [4], we achieve rapid convergence. As shown in *Fig. 6*, **MAPE** and **RMSE** notably decrease within the first **5** iterations and stabilize after **30**. This integration enhances both recovery precision and model convergence speed, significantly improving computational efficiency for large-scale traffic datasets.

Experimental Result

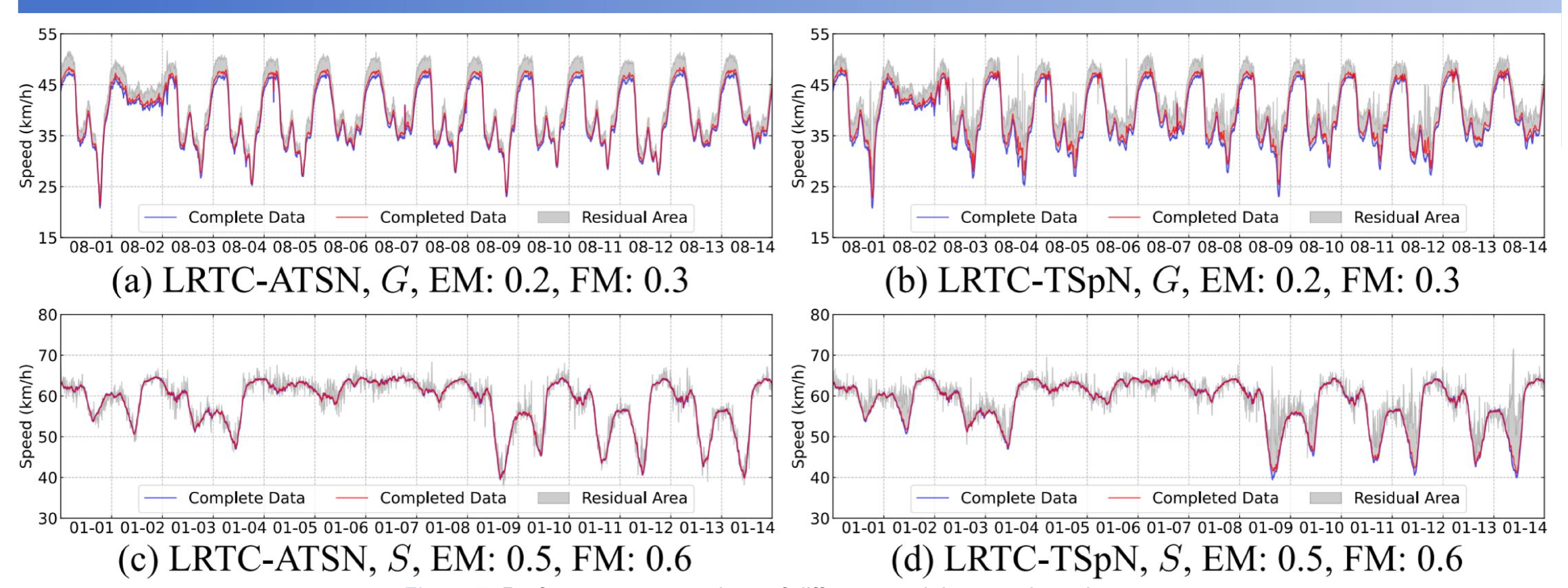

Figure 7. Performance comparison of different models on various datasets

Datasets	Missing Pattern	TMR	BPMF	BGCP	HaLRTC	LRTC-TNN	LRTC-TSpN	LRTC-ATSN
G	EM 0.1 FM 0.1	19.60%	0.106/4.412	0.104/4.321	0.088/3.561	0.073/3.160	0.073/3.132	**0.072/3.097**
	EM 0.3 FM 0.3	48.62%	0.108/4.491	0.104/4.318	0.098/3.929	0.082/3.530	0.081/3.423	**0.078/3.360**
	EM 0.5 FM 0.5	69.75%	0.112/4.665	0.103/4.316	0.109/4.301	0.089/3.849	0.087/3.689	**0.087/3.676**
	EM 0.7 FM 0.7	85.00%	0.119/4.951	0.104/4.320	0.123/4.800	0.098/4.195	0.093/**3.943**	**0.093**/3.947
	EM 0.9 FM 0.9	95.85%	0.139/5.675	0.107/4.473	0.819/33.808	0.111/4.627	0.105/4.409	**0.105/4.355**
S	EM 0.1 FM 0.1	18.52%	0.098/5.526	0.100/5.613	0.071/3.952	0.052/3.329	0.052/3.318	**0.050/3.233**
	EM 0.3 FM 0.3	47.91%	0.099/5.616	0.101/5.615	0.082/4.440	0.060/3.761	0.058/3.583	**0.057/3.582**
	EM 0.5 FM 0.5	69.37%	0.103/5.818	0.099/5.555	0.098/5.078	0.072/4.359	**0.065/3.966**	0.066/4.028
	EM 0.7 FM 0.7	84.80%	0.114/6.327	0.101/5.640	0.121/5.959	0.090/5.274	0.077/**4.531**	**0.076**/4.590
	EM 0.9 FM 0.9	95.78%	0.169/8.529	0.105/5.900	0.200/9.356	0.360/23.742	0.113/6.135	**0.101/5.758**

Best results are marked in bold font. *Table 1. Performance comparison of different models on various datasets*

Tested on real-world datasets from **Guangzhou** and **Seattle**, LRTC-ATSN reduced **MAPE** and **RMSE** by **10.6%** and **6.1%**, respectively, under conditions with up to **95.85%** missing data, while accelerating convergence by over **20%** compared to the best baseline (*Tab. 1*). As shown in *Fig. 7*, LRTC-ATSN further reduced the residual area by **28.3%** on the G dataset (**41.28%** missing) and **36.1%** on the S dataset (**72.21%** missing) compared to LRTC-TSPN.

Conclusion

This study presents LRTC-ATSN, a novel Adaptive Truncated Schatten Norm Low-Rank Tensor Completion model designed to address complex missing traffic data challenges. By integrating dynamic parameter adjustment and adaptive truncation, LRTC-ATSN significantly improves imputation accuracy and efficiency. Evaluated on real-world datasets using a realistic missing pattern generator, it consistently outperforms existing models, even under extreme missing rates. These findings highlight LRTC-ATSN's strong potential to enhance ITS data reliability.

References

[1] Yang, Lei et al. (2024). "A Brief Review on Missing Traffic Data Imputation Methods for Intelligent Transportation Systems". In: *2024 7th International Symposium on Autonomous Systems (ISAS)*. IEEE, pp. 1–6.

[2] Chen, Xinyu, Jinming Yang, et al. (2020). "A nonconvex low-rank tensor completion model for spatiotemporal traffic data imputation". In: *Transportation Research Part C: Emerging Technologies* 117, p. 102673.

[3] Nie, Tong et al. (2022). "Truncated tensor Schatten p-norm based approach for spatiotemporal traffic data imputation with complicated missing patterns". In: *Transportation research part C: emerging technologies* 141, p. 103737.

[4] Xie, Xingyu et al. (2024). "Adan: Adaptive Nesterov momentum algorithm for faster optimizing deep models". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 46(12), pp. 9508–9520.

Contact Information

Haopeng Deng
Looking for 2026 Fall MPhil/Phd opportunities
Research Interests:
Mixed Traffic Dynamics; Urban Mobility Modelling; Multi-agent Control; Spatiotemporal Data Analysis
Email: qianyhp@gmail.com
Homepage: https://qianyhp.github.io/
Scan QR code on the right for homepage details

WeChat

Homepage