Low-Rank Test-Time Training for Pre-Trained Point Cloud Models

Supplementary Material

Table A1. Efficiency comparison on ScanObjectNN-C / ShapeNet-C / ModelNet40-C, evaluated on a single NVIDIA A6000 GPU.

Method	Params (M) ↓	Latency (s/sample) ↓	Memory (MB) ↓
SMART-PC-Online	29.25	0.35 / 0.16 / 0.15	22798 / 8066 / 8106
MATE-Online	29.25	0.23 / 0.22 / 0.20	8878 / 5560 / 5540
LoTT-PC-Online (Ours)	**0.59**	**0.17 / 0.17 / 0.13**	**1174 / 1182 / 1182**

A. Efficiency Experiments

Tab.A1 shows that LoTT-PC achieves efficiency gains: **50**× fewer trainable parameters (0.59M vs 29.25M), **7.5**∼**19.4**× lower memory consumption, and lower latency. These results support its real-world deployment.

B. Limitation

The primary limitation of LoTT-PC lies in the inherent trade-off between adaptation performance and inference latency. Although the proposed design substantially reduces computational overhead by updating only lightweight low-rank modulation units, the need for gradient backpropagation during test-time still introduces extra latency compared to static inference models. While this cost remains significantly lower than that of full fine-tuning, it may nonetheless pose challenges for ultra–real-time applications with stringent latency requirements (*e.g.*, high-speed autonomous driving), where even a few milliseconds are critical.

C. Broader Impact

The research on robust 3D perception has significant implications for real-world applications and societal safety. Our work directly contributes to the reliability and safety of 3D perception systems. By enabling models to adapt to unforeseen corruptions at test time (*e.g.*, sensor noise from rain, snow, or dust), LoTT-PC can enhance the robustness of applications in autonomous driving [1, 2] and robotics [3, 4]. For instance, a self-driving vehicle's LiDAR system could leverage our method to mitigate performance degradation caused by real-time sensor deterioration, maintain accurate scene understanding, and potentially prevent accidents. Moreover, the parameter-efficient nature of our approach makes this level of robustness more feasible for deployment on edge devices with limited computational resources, democratizing access to safer AI.

References

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