V. Conclusion

In conclusion, performance testing on four different datasets reveals that particle filters consistently demonstrate high precision and solid Multiple Object Tracking Precision (MOTP) rates, highlighting their effectiveness in data handling and object matching tasks. Across all scenarios, precision remains impressively high, between 95-99%, and MOTP stays stable around 69-79%, indicating the reliability of particle filters in detecting objects accurately and maintaining consistent performance with minimal false positives. This suggests that particle filters are highly suitable for applications where consistent detection and general object matching are prioritized. For instance, the “Pedestrian Tracking” and “KITTI-17” datasets illustrate the robustness of particle filters in handling objects across frames, emphasizing their stability when precision and matching are key considerations.

However, despite these strengths, particle filters struggle with overall tracking accuracy as reflected in low Multiple Object Tracking Accuracy (MOTA) rates and a high incidence of false negatives. The MOTA scores range from 3.1-7.2% across datasets, while the number of false negatives exceeds 230 to 840 in most scenarios, signifying gaps in their ability to maintain continuous tracking for objects, especially when dealing with occlusions or complex tracking environments. These results suggest that while particle filters excel in initial object detection and data handling, they are less effective in scenarios requiring precise, uninterrupted tracking over time. For applications that demand high tracking accuracy and low false negative rates, such as autonomous vehicles or security monitoring, additional methods or enhancements may be needed alongside particle filters to ensure comprehensive and precise tracking.

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