that gaussian-sum filter is not great when it comes to handling accurate object-related data.

D. Performance Testing on Scenario 4

Scenario 4 uses the "TUD-Campus" dataset. The dataset contains 71 frames. Table V shows that the metric precision is show the best result in some threshold, as it yields a result in around 7.1%-55.5%. The MOTP metic also not very good at the range of 26.8%-37.2%. This illustrates that the Gaussian-sum filter can perform well when it comes to data handling and data matching with the suitable threshold.

Despite the result shown for precision and MOTP, the percentage of MOTA and false negatives if performing badly, resulting in -6.2% of MOTA track rate, and over 50 tracks that are classified as false negatives for each of the results. This estimate that gaussian-sum filter are not very good when it come to handling accurate data.

E. Discussuion

Several studies have discussed the impact of Multiple Object Tracking (MOT). Hayden *et al.* [19] Multiple Object Tracking have critical role in enabling robust data associated for analyzing long-term motion trajectories, in particular complex scenes. Then Jonah *et al.* [20] said that occlusions present a significant challenge in Multiple Object Tracking by obstructing the visibility of objects in a scene, especially in crowded environments with using Aggregated Channel Features (ACF). This study found that complex environments can negatively impact results, as demonstrated by the "TUD-Campus" dataset. Compared to other datasets, the smaller frame sizes and complex object interactions in this dataset significantly reduced the Multiple Object Tracking Precision (MOTP) by -6.2% and resulting false negative to 50 tracks. Our contribution is to understanding Gaussian-Sum Filter performance to be used in object tracking survilance.

Research such as paper [10], have applied Numerous advancements, including advanced measurement updates, combinations of Kalman filters, and Gaussian sum particle filtering, have been developed for target tracking, computer vision, and geoscience applications. This study shows that without advancing or combining algorithms, precision is achieved by 98.9%. This indicates that without advancing or combining algorithms, Gaussian-Sum Filter can maintain high precision in specific environments.

TABLE VI. RESEARCH THAT IS STATE-OF-THE-ART IN GAUSSIAN-SUM FILTER

Cite	Multiple Object Tracking	Gaussian-Sum Filter	ACF
[10]	✗	✓	✗
[19]	✓	✗	✗
[20]	✓	✗	✓
Proposed Methode	✓	✓	✓

IV. CONCLUSION

In conclusion, performance testing on four different datasets reveals that Gaussian-Sum Filter consistently demonstrates strong detection accuracy under specific configurations and using Aggregate Channel Features (ACF). Across all scenarios, precision remains very good in specific datasets, around 7%-98%, and MOTP stays around 10%-73%, indicating the reliability of the Gaussian-Sum Filter in detecting objects accurately and maintaining consistent performance with minimal false positives. This implies that Gaussian-Sum Filter is appropriate for applications where reliable detection and object matching are essential. The datasets "Pedestrian Tracking" and "MOT17-09-SDP" exemplify the robustness of the Gaussian-Sum Filter to track objects across frames, as such stability is crucial for accuracy and matching when objects need to be tracked.

However, despite these strengths, Gaussian-Sum Filter struggles with overall tracking accuracy, as reflected in low Multiple Object Tracking Accuracy (MOTA) rates and false negatives. The MOTA scores range from -6%-10% across the dataset, while the number of false negatives exceeds 4 to 77 in most scenarios, signifying gaps in their ability to maintain continuous tracking for objects, especially when dealing with occlusions or complex environments. These results suggest that while Gaussian-sum filters excel in initial object detection and data handling, they are less effective in scenarios requiring precise, uninterrupted tracking over time. Future research could explore hybrid models combining Gaussian-Sum Filter with other Bayesian filtering to optimize object detection and data handling in complex environments and occlusion problem for increasing tracking accuracy.

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