Detecting Outliers in 3D Point Clouds Using Higher-Order Geometric Cycles for Accurate 3D Reconstruction

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3D point clouds are fundamental to robot perception and 3D reconstruction. However, due to interference, they often contain outliers which distort surface geometry and degrade the performance of downstream tasks such as SLAM. Classical filters (Statistical Outlier Removal and Radius Outlier Removal) rely on local density or pairwise distances to prune outliers. Consequently, such filters do not directly calculate higher-order geometric relationships between points, and as a result, can struggle when point density varies, thin structures are present, or noise is structured instead of random. This research introduces a novel filter that detects outliers by examining higher-order geometric cycles in 3D point clouds. For each point, cycles are formed with its k-nearest neighbors, and each cycle is scored using robustly scaled metrics that determine how much a triangle conforms with its neighbors. Cycles that deviate strongly from the local surface structure receive higher scores, and each point's outlier score is defined as the average score of the cycles it participates in. ? The algorithm was tested on synthetic datasets (plane, sphere, and torus) with 5–10% injected outliers, as well as on the Stanford Bunny dataset that contains predetermined outliers. Across these datasets, the cycle filter achieves significantly higher average F1 scores than SOR and ROR while maintaining lower computational cost than modern ML based approaches. These results demonstrate that analyzing higher-order geometric cycles provides a lightweight, interpretable, and effective way to remove outliers and improve point-cloud quality and thus accuracy of diverse applications such as safe autonomous driving, robotic surgery, and aerial mapping, among others.

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