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Improving Clustering Accuracy for Object Tracking Based on DBSCAN and IoU Techniques

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In recent years, research on automated driving has been conducted with the aim of reducing traffic accidents and easing traffic congestion. Correct recognition of the surrounding environment and accurate tracking of moving objects are important to improve the safety of automated driving. Recognition of the surrounding environment is performed using Laser Imaging Detection and Ranging (LIDAR), which acquires a 3D point cloud, and observation information is obtained based on the clustering of the point cloud by object. However, if incorrect observation information is obtained due to mis-clustering, moving objects cannot be accurately tracked. Therefore, this study proposes two methods to improve mis-clustering, aiming to correct object mis-recognition and make moving object tracking more robust.

The first method is to perform reclustering. Reclustering is performed using Density Based Spatial Clustering of Applications with Noise (DBSCAN), a clustering method based on the density of point clouds. This method corrects the correct number of clusters by re-clustering when multiple objects are erroneously combined into one due to mis-clustering.

The second method uses Intersection over Union (IoU) to perform correspondence correction. Object tracking is performed by mapping existing tracking information with observation information obtained from sensors for each object. However, conventional methods only map objects on a one-to-one basis, so accurate tracking is not possible when an object is split up due to misclustering. Therefore, we decided to map them on a one-to-many basis. First, the IoU of the rectangular box of the existing tracking information and the rectangular box of the observation information that could not be mapped is calculated. Next, if the value is greater than a threshold value, then we determine that the unmatched observation should have been mapped to the existing tracking information. Then, the observation information that was originally associated with the existing tracking information and the observation information that was not associated with the existing tracking information are merged into the new observation information, and the result is as if multiple clusters that were mis-segmented were merged.

The DBSCAN evaluation was performed on actual driving data, using scenes in which two vehicles were inadvertently placed in the same cluster and could not be accurately tracked. On the other hand, the performance evaluation by modification using IoU uses scenes where the clusters split due to occlusion and the tracking was not stable. Both are verified by comparing the ratio of the size of the rectangular box (vehicle length and width) of the existing tracking information to the true value (the value of the vehicle specification). The results are shown in the graph. In both scenes, only the change in vehicle length is shown in the graphs, since there was little change in vehicle width with or without the proposed method. First, here are the DBSCAN validation results (Figure 1(a)). The maximum error in vehicle length was 170% of the true value, but the error was reduced by 154% for the re-clustered model. Next are the results of the validation of the correction using IoU. The maximum error in vehicle length was 64% of the true value, but the error was reduced by 38% for the one with the correction.

In a scene where the size of the rectangular box was not correctly recognized due to incorrect cluster information and accurate tracking was not possible, the proposed method was able to suppress the time-series variation of the rectangular box size and improve the robustness of the object tracking.

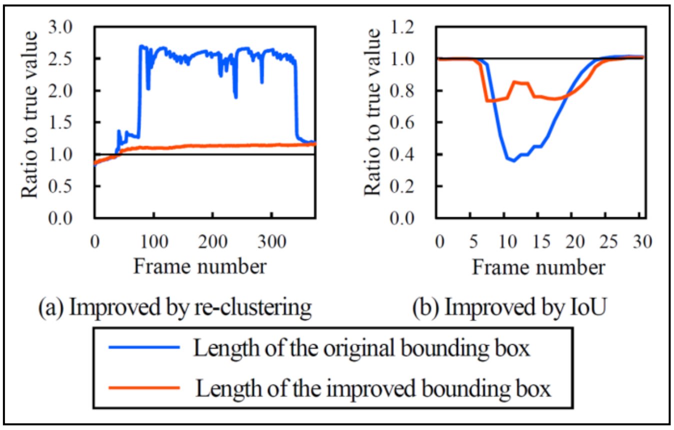

Fig.1 Comparison of bounding box sizes (Car length)