



# Poster: Fast Field-of-View Expansion for Collaborative Object Detection

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## ABSTRACT

As interest in autonomous driving and advanced driver-assistance systems (ADAS) has grown, various sensing technologies have been developed to accurately determine the position and situation of surrounding vehicles and objects. In particular, *light detection and ranging* (LiDAR) sensors have attracted attention and are widely used in autonomous driving and ADAS because of their accuracy and reliability. However, when LiDAR sensors are used on a single vehicle, they can encounter blind spots caused by obstacles, which limits the detection of the environment. To overcome this issue, a method that can register and identify objects using LiDAR data from multiple vehicles in real-time is needed. Conventional artificial intelligence and *iterative closest point* (ICP) approaches need faster processing speed for practical use. Therefore, this work proposes an object-based *single-point ICP* (SP-ICP) which enables faster processing while maintaining accuracy using only a single point centered on each of the objects.

## CCS CONCEPTS

• Computing methodologies → Multi-agent systems.

## KEYWORDS

Object Detection, Field-of-View Expansion, Collaborative Sensing.

## 1 INTRODUCTION

As interest in autonomous driving and advanced driver assistance systems (ADAS) grows, there has been significant development in sensing technologies to assist vehicles and their drivers. Among these technologies, *light detection and ranging* (LiDAR) stands out for its high precision and reliability in detection, making it a widely researched and utilized sensor in autonomous driving. However, LiDAR sensors installed on individual vehicles alone cannot effectively perceive environments visually obstructed by obstacles.

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2022R1A4A5034130), and also by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2024-RS-2022-00156353) supervised by the IITP (Institute for Information & Communications Technology Planning & Evaluation).

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Mobisys '24, June 3–7, 2024, Minato-ku, Tokyo, Japan

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ACM ISBN 979-8-4007-0581-6/24/06.

<https://doi.org/10.1145/3643832.3661420>

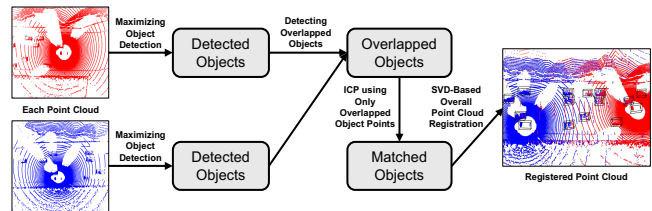


Figure 1: Overall workflow of SP-ICP

Thus, a method is needed to identify objects in real-time through the registration of point cloud data from other vehicles. However, conventional methods such as *iterative closest point* (ICP) [1] and AI/ML-based approaches are too slow to use in practice.

To address this problem, this work proposes object-based *single-point ICP* (SP-ICP) which rapidly registers and expands point cloud data for objects detected by vehicles. SP-ICP detects objects within point clouds, identifies common objects based on relationships, and performs ICP based on these overlapping points (Fig. 1). Also, it improves upon existing object recognition algorithms such as PointPillars [2] by modifying parameters of the loss function to minimize missing objects even as the number of falsely recognized objects (False Negatives, FN) increases. As a result, vehicles can more accurately perceive their surroundings, thereby enhancing the accuracy and reliability of autonomous driving and ADAS.

## 2 DESIGN

The key components of SP-ICP are robust object detection and single-point ICP based the detected objects.

**Robust Object Detection:** We enhance the performance of object detection by minimizing the rate of missed actual objects. Despite the focus of numerous existing object recognition methods on the accuracy of vehicle detection, efforts to minimize false detections can paradoxically lead to the omission of actual objects. For autonomous driving and safe driving environment, avoiding missing actual objects is far more critical than reducing false detections. Therefore, even if the false detection of objects increases, we have adjusted parameters such as the loss function and the intersection over union (IoU) of PointPillars to enable broad recognition without missing actual objects.

To achieve this, we adjusted the parameters of the Focal Loss [3]:  $\mathcal{L}_{cls} = -\alpha_a (1 - p^a)^\gamma \log p^a$ .  $\alpha$  and  $\gamma$  are parameters used to adjust the weight based on class imbalance and detection difficulty, respectively. To reduce FN, we increased the value of the parameter  $\alpha$ , which adjusts the prediction weight for minority class objects, from 0.25 to 0.3. This measure aims to enhance the model's sensitivity

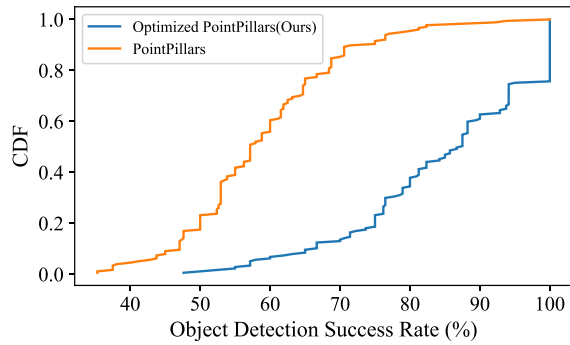


Figure 2: Detection rate compared to ground truth

to actual objects. Additionally, we adjusted the value of  $\gamma$  from 2.0 to 3.0 to increase the model's responsiveness to difficult examples. Furthermore, to increase the total number of detected objects, we adjust the threshold of the IoU used to determine the presence of an object to 0.4. This adjustment allows the model to detect a broader range of objects, thereby increasing the comprehensiveness of object detection.

We improved the performance of the object detection model by modifying parameters such as the loss function and the IoU threshold. The results after training showed a notable decrease in the rate of missed actual objects, as illustrated in Fig. 2.

**Single-Point ICP:** The primary goal of this work is to enable the real-time processing of point cloud data collected from multiple vehicles, addressing the practical limitations faced by existing AI/ML-based and ICP-based approaches in terms of processing speed or accuracy.

To enhance processing efficiency, our SP-ICP approach introduces a novel method that leverages only the centroid of each object for ICP calculations. It identifies objects based on their centroids, and utilizes GPS data to align the initial positions of the point clouds. After analyzing distances and angles between object nodes, along with examining their relational attributes, identical objects are identified. The ICP is then performed using these identified objects, enabling accurate registration with a minimal number of points. Through singular value decomposition (SVD), the remaining points are aligned with the previously registered translation and rotation matrices, allowing for rapid and efficient registration. Adopting this strategy permits the execution of ICP computations with the fewest possible points, corresponding to the number of vehicles involved, thereby drastically reducing repetitive operations and ensuring a swift processing speed.

This design is particularly well-suited for applications requiring the real-time integration and analysis of extensive point cloud data from diverse sources. It represents a significant improvement over existing methods in terms of efficiency and scalability, offering a robust solution for advanced object detection and registration challenges.

### 3 PRELIMINARY RESULTS

We evaluate the performance of SP-ICP by comparing it against the conventional ICP and O-ICP [4]. The dataset used was the OPV2V

Item	Method	SP-ICP	O-ICP	ICP
Avg # of Points before Removal		57186.06		
Avg # of Reduced Points		24.71	797.16	17947.29
Avg # of Remained Points Ratio (%)		0.04	1.39	31.38
MAE (m)		0.37	0.63	3.65
mAP		0.84	0.71	0.28
Time (ms)		261.22	786.47	6043.85

Table 1: Comparison of SP-ICP, O-ICP, ICP

[5], which consists of point cloud data suitable for vehicle-to-vehicle communication research, generated using a simulator.

Table 1 presents the result. O-ICP performs ICP using all points in a specific range around the object, which is different from SP-ICP that utilizes a single point at the center of each object for registration. Therefore, it can be observed that the number of points used during the ICP process is extremely low for SP-ICP compared to O-ICP. The mean absolute error (MAE) measured from the distance errors between detected objects showed that SP-ICP, O-ICP, and ICP, in that order, exhibited the lowest errors. Additionally, in terms of the mean average precision (mAP), which represents the average precision of the IoU values indicating the extent of overlap in object detection areas, SP-ICP demonstrated the best performance.

Lastly, the time taken for the registration process is also the shortest with SP-ICP. This approach minimizes the number of points used, effectively reducing the number of iteration processes and ensuring a fast registration process. Our findings reinforce the efficacy of SP-ICP in robust object detection and registration processes, outperforming existing methods in accuracy, precision, and efficiency.

### 4 CONCLUSION

In this study, we propose a method for fast registration of LiDAR point clouds by performing single-point ICP only on recognized overlapped objects using a technique that minimizes missed objects. Preliminary results demonstrate that SP-ICP can register objects more quickly and accurately than O-ICP and ICP. As future work, we aim to refine the identification of closely positioned nodes in overlapping objects. By exploring diverse techniques, we plan to improve the precision of selecting overlapped objects, enhancing overall reliability.

### REFERENCES

- [1] K Somani Arun, Thomas S Huang, and Steven D Blostein. 1987. Least-Squares Fitting of Two 3-D Point Sets. *IEEE Transactions on pattern analysis and machine intelligence* 5 (1987), 698–700.
- [2] Alex H Lang, Sourabh Vora, Holger Caesar, Lubing Zhou, Jiong Yang, and Oscar Beijbom. 2019. Pointpillars: Fast encoders for object detection from point clouds. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 12697–12705.
- [3] Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár. 2017. Focal loss for dense object detection. In *Proceedings of the IEEE international conference on computer vision*. 2980–2988.
- [4] Junhyeong Ryu, Christina Suyong Shin, and Jeongyeup Paek. 2023. Iterative Closest Point of Object-based Point Clouds for Multi-View Extension. In *2023 14th International Conference on Information and Communication Technology Convergence (ICTC)*. IEEE, 543–545.
- [5] Runsheng Xu, Hao Xiang, Xin Xia, Xu Han, Jinlong Li, and Jiaqi Ma. 2022. Opv2v: An open benchmark dataset and fusion pipeline for perception with vehicle-to-vehicle communication. In *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2583–2589.