PhD Forum Abstract: Cooperative Perception System with Roadside Assistance

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ABSTRACT

In this paper, we mainly focus on cooperative perception systems for vehicle-road coordination. Specifically, this paper encompasses two main aspects: 1) discussing the spatio-temporal synchronization issues among roadside multiple LiDARs. In this part, we design a method to synchronize the spatio-temporal data among multiple LiDARs by matching trajectory points between them; 2) designing a cooperative perception system based on uncertainty. In this part, we design a scheme to reduce the communication volume of cooperative perception by lowering the communication frequency.

KEYWORDS

Cooperative perception, Spatio-temporal synchronization, Roadside multiple LiDARs, Uncertainty, Communication volume reduction

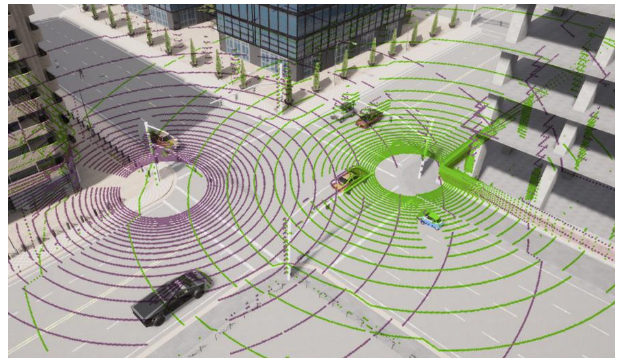

Figure 1: An example deployment of the roadside traffic monitoring system. The point clouds from the two LiDARs diagonally deployed in a 4-way intersection.

1 A METHOD FOR AUTOMATIC CALIBRATION OF ROADSIDE MULTIPLE LIDARS.

The first work I'd like to share with everyone is a method for automatic calibration of roadside multiple LiDARs. In intelligent transportation systems, setting up sensors on the roadside can provide additional information from different perspectives, better monitoring the state of traffic flow. Specifically, LiDARs are increasingly deployed for such purposes due to their ability to provide accurate ranging information that is particularly important for traffic monitoring. However, due to the physical characteristics of LiDAR itself, it is susceptible to obstruction. To address this issue, it has become a common practice to deploy multiple LiDARs in a collaborative manner. In Fig.1, we show a scenario of multiple LiDARs collaborating, where intelligent roadside infrastructures equipped with computing and sensing units capture real-time environment data and perform necessary calculations such as detection and tracking, finally, they will transfer the data to a smart traffic server(STS), where their data will be fused.

This work addresses the problem of spatio-temporal calibration for sensors installed on the infrastructure, which allows for the effective integration of data from multiple LiDARs at various locations, thereby providing a more comprehensive traffic overview.

We note that there are few studies on calibrating roadside multiple LiDARs. [4] Although there exist some methods to calibrate LiDARs, they don't work for roadside because of their own limitations. For the space dimension, most studies have focused on the calibration of the two sensors in space, and assumed that the time between sensors has been synchronized [4, 9, 12]. There are mainly two types of methods of space calibration, target-based, and targetless-based. The target-based methods require identifiable objects (such as checkerboards, polygonal boards, and apriltags), and estimate the relative pose between sensors by aligning the target positions observed on each sensor [8, 12, 13]. These methods require pricey and lengthy manual operations, and cannot be applied to large-scale deployment. As for the targetless methods, they usually extract the features from the environment, and then match the features based on their similarity to construct the constraints required for calibration. The methods of feature extraction face two common challenges in road-side scenarios: 1. Road-side point clouds are relatively sparse, making it difficult to extract geometric features; 2. In traffic scenes, there are many repeated structures, which makes feature matching difficult [3].

With the above challenges in mind, this paper focuses on developing a system that can automatically calibrate LiDARs on the roadside both temporally and spatially. The primary concept is to use trajectory information of moving objects, provided by the point cloud-based object detection/tracking module, to identify correspondences between trajectories captured by different LiDARs.

The main idea is to automatically calibrate the sensors based on the result of the detection/tracking task, rather than relying on extracting special features. Furthermore, we propose a novel mechanism for evaluating calibration parameters that align with our algorithm, and we demonstrate its effectiveness through experiments. This mechanism can also guide parameter iterations for multiple calibrations, further enhancing the accuracy and efficiency of our calibration method. Finally, to evaluate the performance of our method, we collected two datasets, one simulated dataset and one real-world dataset. The experimental results show that our method can achieve a spatial calibration error of less than $10cm$ and a temporal calibration error of less than $1.5ms$ without initial parameters.

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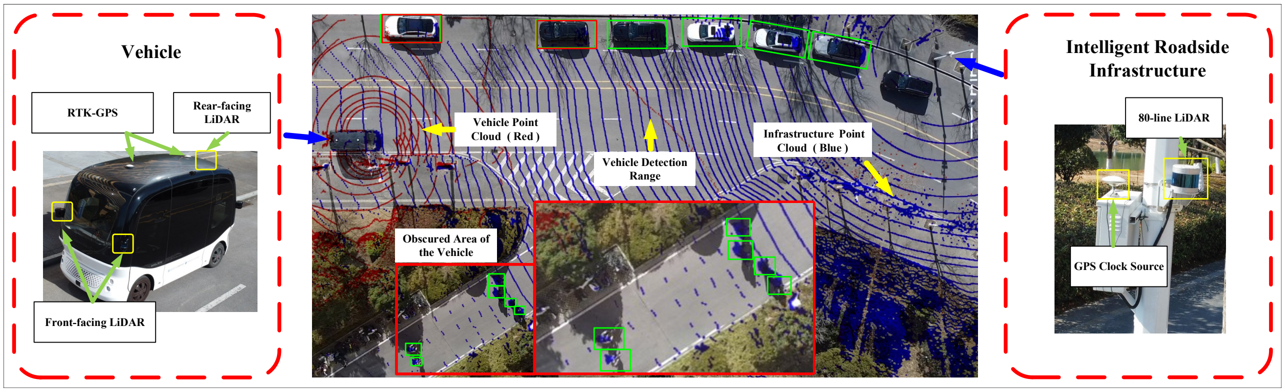

Figure 2: A scenario where cooperative perception enhances safety.

2 AN UNCERTAINTY-AWARE PROACTIVE COLLABORATIVE PERCEPTION SYSTEM

In the first work, we successfully achieved the calibration of multiple roadside LiDARs, thereby enabling the fusion of information from roadside LiDARs. Furthermore, we continue to explore how to utilize roadside data to assist vehicles in collaborative perception.

Autonomous driving vehicles are considered the future primary means of transportation. The relevant technologies in autonomous driving, such as detection [2, 5], have made significant progress. However, there is still considerable controversy about its safety and reliability [6, 7]. Particularly in recent years, there have been several traffic accidents stemming from errors or delays in detection [1, 11]. The core reasons behind these accidents are not only due to the insufficient performance of sensors and algorithms on vehicles but, more fundamentally, stem from the inherent limitations in the perception of a single vehicle, such as blind spots caused by obstruction and a restricted perception distance.

Cooperative perception has attracted increasing attention from researchers in recent years [10, 14]. Based on the different types of shared data, these approaches can be categorized into three types: pre-fusion schemes that share raw data [14], feature fusion schemes that share feature maps, and post-fusion schemes that share perception results [10]. An important challenge for the system is network communication bandwidth. The communication bandwidth of the vehicular network is very limited and cannot meet the requirements for transmitting raw sensor data. If we simply share the raw point cloud data for each frame, the required bandwidth is approximately 184 Mbps (Sending an 80-line LiDAR point cloud at a frequency of 10Hz), which is approximately six times the maximum 5G wireless communication bandwidth we tested(based 20Mhz bandwidth).

To solve this issue, balancing the accuracy of detection and the insufficiency of communication resources, we plan to reduce the communication overhead required for cooperative perception in two ways. Specifically, 1, to reduce spatial interaction, we propose to use network detection methods to extract areas where vehicle information is sufficient and insufficient, to decide which parts of the vehicle's information need to interact. 2, similarly, we consider using network methods to evaluate the timeliness of information, so that information interaction is only reinitiated when the information from the last interaction becomes outdated.

3 BIOGRAPHICAL INFORMATION

I am currently pursuing a PH.D. degree at the School of Computer Science, University of Science and Technology of China. My professor is Prof. Yanyong Zhang. My doctoral degree started in 2020 and is expected to graduate in June 2025. My research interests mainly include sensor spatio-temporal calibration, 3D object detection, and tracking. Currently, I am mainly working on building a cooperative perception system with roadside assistance. Next, I will introduce some of my current work.

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