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Online urban object recognition in point clouds using consecutive point information for urban robotic missions

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HIGHLIGHTS

- The online processing is achieved in order to cope with streaming point cloud data.
- The classification results contain probabilistic outputs in terms of confidence levels.
- It is available to train the classifier with a few examples based on generative model.

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ABSTRACT

Urban object recognition is the ability to categorize ambient objects into several classes and it plays an important role in various urban robotic missions, such as surveillance, rescue, and SLAM. However, there were several difficulties when previous studies on urban object recognition in point clouds were adopted for robotic missions: offline-batch processing, deterministic results in classification, and necessity of many training examples. The aim of this paper is to propose an urban object recognition algorithm for urban robotic missions with useful properties: online processing, classification results with probabilistic outputs, and training with a few examples based on a generative model. To achieve this, the proposed algorithm utilizes the consecutive point information (CPI) of a 2D LIDAR sensor. This additional information was useful for designing an online algorithm consisting of segmentation and classification. Experimental results show that the proposed algorithm using CPI enhances the applicability of urban object recognition for various urban robotic missions.

1. Introduction

Recently, robots have successfully performed various urban robotic missions such as self-driving [1], surveillance [2], and rescue missions [3]. In the urban robotic missions, a robot can be operated by mission level teleoperation [4]. In the mission level teleoperation, a robot generates an environmental map and makes decisions by itself, while an operator simply sets goal points and gives commands by sentence-like descriptions, for instance, go to the building through the roadside trees; if there is a parked car in front of the building, then raise the alarm immediately.

To achieve mission level teleoperation, a robot has to prepare various robotic technologies, namely perceiving environments [5], simultaneous localization and mapping (SLAM) [6], and path planning [7]. Among these, the ability to perceive environments plays an important role in making decisions for navigation policies. It is true that the more various the missions, the more sophisticated the perception ability is required.

With the help of laser scanners (also called light detection and ranging, or LIDAR for short), a robot can collect range information about its environment, as shown in Fig. 1. (In Fig. 1, the red and green lines denote scanning rays of the left and right 2D LIDAR sensors, respectively. The white line denotes the robot's path. The point clouds are painted with corresponding pixels of captured images. Note that camera images are not used for the proposed method.)

However LIDAR provides only spatial information in the form of 3D point clouds without any information about urban objects. With machine learning techniques [9], the information about urban objects can be extracted by labeling point clouds according to kinds of urban objects. This technique for labeling point clouds is referred to as urban object recognition or scene analysis [10]. Urban object recognition techniques have been researched in the robotics community [10–18] and the computer vision community [19,20] as well.

In spite of many previous works in urban object recognition, it is still hard to apply it to urban robotic missions due to several

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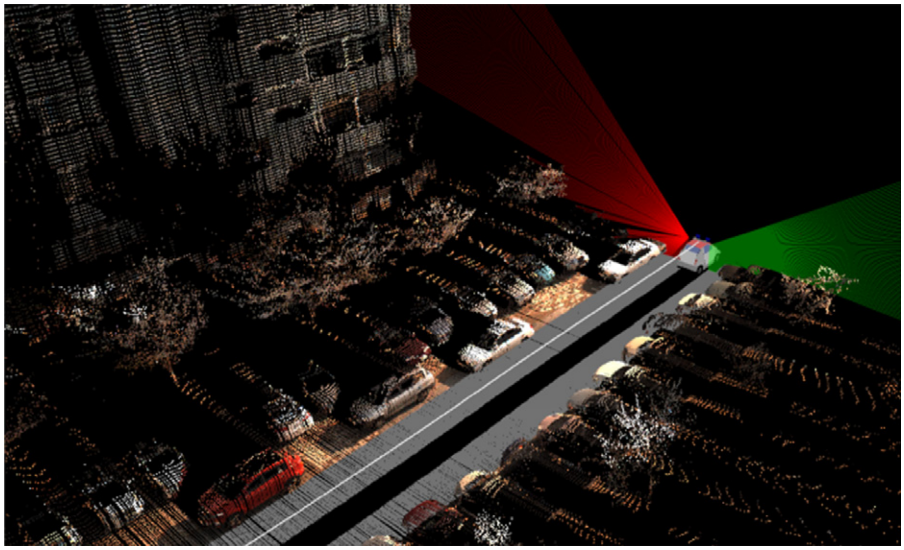

Fig. 1. Screenshot of our urban robot scanning in urban environments. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

difficulties: offline-batch processing, deterministic results in classification, and necessity of many training examples. The aim of this paper is to propose an urban object recognition algorithm which solves the difficulties. To achieve this, the proposed algorithm utilizes the consecutive point information (CPI) which can be obtained from the sensor configuration of 2D LIDARs shown in Fig. 1. The sensor configuration is a popular choice in urban robotics [13,18,21,22]. In this paper, it is shown that the CPI is useful in the design of an online algorithm consisting of segmentation and classification.

The paper is organized as follows. In Section 2 the difficulties of previous works in urban object recognition and our contributions are described. In Section 3 we then propose an online urban object recognition algorithm based on a two stage framework, which consists of a segmentation and classification step. Subsections in Section 3 gradationally describe a 2D LIDAR sensor system, an outline of the proposed method, point type extraction, segmentation, and classification. In Section 4 we then explain the experimental setup and show experimental results with quantitative tests in terms of segmentation performance, classification performance, and time consumption. In Section 5 a discussion of urban robotic applications and conclusions are given.

2. Related work

Urban object recognition techniques can be categorized as sensors, such as vision-based solutions [15], LIDAR-based solutions [10,13,16–19] or fusion solutions using both vision and LIDAR [11,12,14,20]. In comparison with a vision sensor (camera), a LIDAR sensor is more robust to illumination changes and provides more precise 3D range information. For such reasons we regarded LIDAR as the preferable sensor in urban environments.

Depending on whether or not moving objects are included, the environments of previous studies can be divided into static or dynamic scenarios. In dynamic environments, the previous studies [23,24] concentrated on classifying moving objects such as bikes, moving cars, and pedestrians, or tracking moving objects in order to predict paths of moving objects and to avoid them. Our final goal is to propose an urban object recognition algorithm to be used for various urban robotic applications such as surveillance and SLAM. Our scenario requires that various kinds of urban static objects such as buildings, trees and parked cars are perceived.

The results of urban object recognition can be obtained by labeling 3D point clouds with predicted classes. Most methods [10–20] follow a supervised learning procedure [9] which consists of a training step and a testing step. In the training step, a classifier was previously trained with features that can be extracted from 3D point clouds and/or 2D images and with true class labels. In the testing step, the trained classifier predicts class labels of the testing point clouds and/or images.

In computer vision, previous studies for urban object recognition have achieved good performance in terms of successful classification rates [19,20]. In robotics, however, one should consider other requirements that need to be performed in robotic missions. Here we discuss the following requirements in order to make urban object recognition applicable to real robotic scenarios.

Online processing

In many previous studies [10,13,14,16,17,19] it was assumed that point clouds were given after the environments were scanned. This method via off-line batch processing is intractable in coping with streaming point clouds that are newly incoming while a robot scans the environment by LIDAR as shown in Fig. 1. In urban robotic missions such as surveillance and SLAM, it is important to detect urban objects as soon as possible in order to make quick decisions. Therefore it requires an online algorithm which can produce classification results by processing streaming point clouds before observing whole point clouds.

In the offline methods, the main difficulties for online processing are iterative computation and complex graphical models in structured prediction. Structured prediction is a popular approach for urban object recognition in which point clouds are built to a graphical model based on a random field structure [25]. The graphical model performs iterative computation such as linear and quadratic programing for training and inference respectively. For random fields based methods [10,12,14,15,18–20] it is intractable to perform iterative computation in a complex graphical model. Due to the requirement of online urban object recognition, recent studies focus on overcoming the drawbacks of random fields based methods. Munoz et al. [26] proposed a simplified computation for inference. Hu et al. [18] proposed an online algorithm by grid based approximation which can process streaming point clouds.

Another popular approach is the two stage framework consisting of segmentation and classification steps [11,13,16,17]. In the segmentation step, point clouds are split into several clusters according to urban objects. In the classification step, each cluster