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Plane-based scan registration with moving vehicles exclusion

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ABSTRACT

Moving vehicles have a considerable negative effect on the accuracy of scan registration and lidar odometry. To remove the negative effect, we propose an extended 2D virtual scan to obtain all moving objects in the sensing range of lidar by a scan differencing operation between two consecutive scans. The dynamic objects' poses are estimated with our proposed likelihood-field-based vehicle measurement model and the motion evidence is utilized to classify the objects as moving vehicles or not. In this way, the moving/dynamic vehicles are detected and the points hitting them are removed. The remaining points are then taken as an input into the alignment.

In the registration, we adjust the raw distorted points by modeling the lidar motion as the constant angular and linear velocities within a scan interval, and then exploit the probabilistic framework to model the local plane structure of the matched feature points instead of the original point-to-point mode. The transform is achieved by the combination of coarse motion estimation and fine batch adjustment. The algorithm has been validated by a large set of qualitative tests on our collected point clouds and quantitative comparisons with the excellent methods on the public Karlsruhe Institute of Technology and Toyota Technological Institute (KITTI) odometry datasets.

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1. Introduction

Data registration is a hot research topic in several key technologies of autonomous driving, e.g., visuar/lidar odometry, scene understanding and common simultaneous localization and mapping (SLAM). The algorithms of alignment rely on the static point clouds in overlapping regions to optimize the rigid transform between two consecutive frames or between the frame and accumulated map. Owing to lidar's insensitivity of lighting changes, and high frequency depth measurements where errors are relatively constant irrespective of the distance traveled, different kinds of lidars [1–3], especially, Velodyne HDL-64E scanner [4,5], have been widely applied in the field of self-driving.

Moving/dynamic objects have great effects on the accuracy of scan registration, and the accumulated incremental error over time is bound to drift in the following lidar odometry. One natural idea to reduce the drift is to remove moving objects in the alignment. This refers to the classical problem of detection and tracking of moving objects (DATMO). There are some differences between DATMO in the aspects of the safe autonomous navigation (marked as General DATMO) and the alignment or odometry (marked as Aligned DATMO).

(1) Processing range. The critical threat for safe autonomous navigation comes from the closest obstacles which possibly induce potential collision, whereas the further away obstacles have little or even no effects on driving safely. Thus many approaches in the general DATMO only record and process the closest obstacles [6,7], which are reasonable and efficient. However, the registration is expected to use the total point cloud [8–10] or the features extracted in the whole scene [11] to match, and thus those points hitting the more distant obstacles must be taken into consideration. This demands that the aligned DATMO methods extend the processing range to the total scene.
(2) Processing scan number. To achieve a robust and reliable output, the general DATMO methods [7,12] are first to detect the moving objects in the current scan and then to gradually validate by tracking. The process will take several scan periods or even more to accomplish [13]. This strategy is not suitable for our application. Moving objects generate negative effects on scan registration before they are distinguished through sequential tracking and unfortunately, the error cannot be

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removed once it appears. Thus for registration or odometry, what it really needs is to find moving objects and remove them within just two scans.

(3) Processing objects. To avoid collision, the general DATMO approaches [6,14,15] need to process common moving objects such as vehicles and pedestrians, whereas the aligned methods [16] are usually only interested in the moving vehicles, either because the velocity of the pedestrian is relatively low (about 1–2 m/s), which may be covered by the noise from the measurement and model, or because the number of points hitting the pedestrian is relatively small due to their small volumes. In this paper, we only consider the removal of moving vehicles at present.

(4) Tolerant recall. The general DATMO algorithm has a high demand for recall because any false negative can possibly induce danger for the autonomous ground vehicle. By contrast, misjudge stationary objects as moving ones on account of not tracking and not using those points falling on them will have little or no effects on the matching performance. This is because the misjudged points can include only a very small portion in the total abundance of points from Velodyne HDL-64E.

Based on the four differences discussed above, in this paper, we propose an extended 2D virtual scan to handle all moving objects in the scene, which overcomes the drawback of the original virtual scan [7] only recording the closest obstacles. For each moving object, its pose is estimated with our novel likelihood-field-based vehicle measurement model, and the motion evidence proposed in [7] is utilized to validate the moving object to be the vehicle or not, in just two consecutive scans. Because the vehicles are restricted to moving on the 2D ground surface, some vehicles, visible in the 3D space, could be occluded in the 2D space. Our proposed algorithm can deal with the pose estimation of all the moving vehicles in the whole scene, while [7] and its variant [17] cannot. The detected moving vehicles are removed and the remaining point cloud is taken as an input for our novel scan registration algorithm.

The readings collected by the Velodyne HDL-64E are distorted when the lidar itself is moving. In this paper, we model the lidar motion as the constant angular and linear velocities during a scan interval, and compensate the raw distorted point cloud by linearly interpolating the initial pose transform (provided by the wheel encodes). The lidar collects over 130,000 3D points per scan. To reduce the computational complexity, we use the same approach as in Ref. [11] to extract feature points located on sharp edges and planar surfaces, and match them to the points projected in edge line and planar surface patches, respectively. However, the point-to-point metric criterion does not consider the geometric attribution of the local neighborhood of the selected point. Based on this, we exploit a probabilistic framework [9] to model local plane structure which ensures a high confidence in the normal direction. The estimation of pose transform is achieved by the excellent coarse-to-fine strategy [11]. Integrating with the removal of all moving vehicles, our aligned method can obtain higher performance in comparison with the excellent methods [9,11,18].

There are two main contributions in our paper: one is the likelihood-field-based vehicle measurement model, which can deal with the pose estimation of the vehicle; the other is the plane-based metric criterion in the alignment process, which can match well the lidars feature points. The first contribution is the more significant one.

The rest of the paper is organized as follows. In the next section, a survey of related works is summarized. After that the moving vehicle detection algorithm in two scans is presented in detail in Section 3. The novel scan registration algorithm is described in Section 4. The experimental results and analysis are shown in Section 5. Finally, Section 6 gives the conclusions.

2. Related works

Moving vehicles have a great negative effect on the accuracy of scan registration and lidar odometry. To remove this effect, the detection of moving vehicles is needed. Current methods generally can be divided into two categories: feature-based methods [19–23] and model-based methods [7,13,17].

In [19], the radar data was accumulated in an occupancy grid where the objects were detected. The candidate object was validated as the parked vehicle using four features with two random forest classifiers. Ref. [20] proposed three geometric features for the finely segmented 3D object to classify the vehicles with the kernel support vector machine (SVM). Ref. [21] exploited the distance criterion to cluster the obstacle points and fitted the cluster in a cube bounding box. The length, width and height were utilized to classify the cube box into a vehicle or not. In [22], the contour information, i.e. the ratios of length to height and width to height of the object bounding box, was employed to detect the vehicles. The RANSAC approach was implemented in [23] to fit a straight-edge feature with "L-shape" to detect the vehicle. The common flowchart of feature-based methods consists of segmentation, cluster similarity, feature detection and model fitting. The main drawback lies in that, with noisy and cluttered data, there are many ambiguities in fitting a vehicle.

The model-based methods generally exploit the cuboid or rectangle to fit a vehicle. Ref. [17] proposed a view-dependent adaptive matched filter algorithm to obtain a vehicle pose. It took self-occlusion into account and used four rectangles to represent two visible sides, the interior and the exterior regions of a vehicle, respectively. A gradient-descent-based optimization was used to maximize the integrals over the four rectangles. In [7], the pose of a moving vehicle was estimated with a Bayesian filter and every particle was weighted with the rectangular measurement model, then the motion evidence was used to quickly prune false positives caused by noise. Ref. [13] extended the work in [7] to overcome the unavailability of road network information and introduced geometric and temporal cues to reduce the sampling range for improvements to efficiency. The geometric model in [7] and its variant [13] can only detect the closest vehicles. This model is unsuitable to our scan registration that requires all moving vehicles to be removed. We focus on this problem in this paper.

In scan registration, selecting a small quantity of basic elements from the richness of points and using a reliable criterion to match is an effective way to reduce computational complexity and improve robustness. One popular idea is to extract reliable features to align. Various features have been applied, i.e., the key point [24], the spin image [25], FPFH [26], NARF [27], and the rectangle-based histogram [28]. The feature-based algorithms can deal with scan pairs with partial overlap and large offset, but take a large amount of time on the computation of feature descriptors and lack proper strategies to remove the incorrectly matched features. Recently, Ref. [11] proposed a simple and efficient method to select points located on distinct edge lines and planar surfaces according to points' curvatures. In this way, it can reduce the number of matched pairs to a lower level.

The golden standard for precise alignment was the iterative closest point algorithm (ICP) [18], which attempted to optimize the transform in the point-to-point way. One common assumption is that a good original guess is available, otherwise it is easy to get trapped in local minima. Ref. [9] proposed a novel criterion to describe the point pairs in a probabilistic form and modeled a locally planar surface structure from both scans. A major problem of point-based methods is the expensive computation of the nearest-neighbor correspondences [29]. Considering the shortcoming, three-dimensional normal distributions transform (3D-NDT) was presented in [10] and later expanded from point-to-distribution to distribution-to-distribution [30]. NDT can also

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