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Accelerated patch-based planar clustering of noisy range images in indoor environments for robot mapping

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ABSTRACT

This paper introduces a methodology to cluster noisy range images into planar regions acquired in indoor environments. The noisy range images are segmented based on a Gaussian similarity metric, which compares the geometric attributes that satisfy the coplanarity conditions. The algorithm is designed to cluster coplanar noisy range data by means of patch-based sampling from range images. We discuss the advantages of patch-based clustering over point-based clustering of noisy range images that eliminates computational redundancy to accelerate the clustering process while keeping the segmentation error to a minimum. The final output of the algorithm is a set of polygons, where each polygon is defined by a set of boundary points that replaces large number of coplanar data points in a given planar region. The 3D range image is acquired by a rotating 2D range scanner and stored in a 2D array. Each element in the array is explicitly stored as the range distance; the indices of the array implicitly retain neighborhood and angular information. The array is grouped into mutually-exclusive patches of size $(k \times k)$ and the Hessian plane parameters are computed for each patch. We propose a graph-search algorithm that compares the plane parameters of neighboring patches by searching breadth-wise and clusters the coplanar patches into respective planes. We compare the proposed Patch-based Plane Clustering (PPC) algorithm with the point-based Region Growing (RG) algorithm and the RANSAC plane segmentation method to analyze the performance of each of the algorithms in terms of speed and accuracy. Experimental results indicate that the PPC algorithm shows a significant improvement in computational speed when compared with the state-of-the-art segmentation algorithms while maintaining a high accuracy in segmenting noisy range images.

1. Introduction

1.1. Motivation

3D range scanners acquire range images, which essentially outputs range distance measurements between the sensor and the surrounding environment. This paper deals with real-time processing of range images acquired in indoor environments, which consists of mostly planar surfaces. A range image represented in the spherical coordinate system can be converted to a 3D point cloud representation in the Cartesian coordinate system and vice-versa. This conversion is even applicable to multiple overlapping 3D point clouds, which are an outcome of 3D registration [1]. For robotic applications, it is desirable to have a more compact representation of range images, which can be achieved by extracting polygon features defined by a set of boundary points leading to compression of range maps. Polygon extraction from noisy range images is a challenging task and the polygonal model of the environment is useful in robotic applications such as 3D mapping and robot navigation in indoor environments. The current commercial 3D range scanners used in robotic applications are capable of acquiring large number of data points ($N > 10^4$) in a short period of time (<30 s). This data acquisition is achieved by spinning the 2D range scanner on a rotating platform. The angular resolution of the range image is limited by the resolution of the motors spinning the range scanner. Most conventional range scanners used in robotics are inexpensive but noisy. Their range measurement accuracy is dependent on a number of factors including range sensor limitations, embedded processors in the scanning equipment, step accuracy of internal and external motors driving the range sensor and reflection/refraction of the laser beam on different surfaces. The high-resolution range scanners are accurate but they are normally bulky and expensive. Our research makes use of less expensive light-weight range scanners, namely the Hokuyo® URG-LX and the UTM-30LX 2D range scanners that can be mounted on

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wall climbing robots [2] and miniature Quadraptor helicopters [3], which have constraints in payload and on-board computational power.

The range data acquired by 3D range scanners consists of large amounts of digital information that needs memory storage space and should be further processed in real-time for a number of robotic applications such as 3D scan registration with polygons [4,5], digitization of indoor environments [6], 3D map construction [7] and robotic navigation. Feature-based representation such as polygon representation of range images is advantageous over point-based representations in a number of ways. The polygonal maps occupy less storage space compared to 3D point clouds/range images. Efficient memory storage is achieved by replacing large numbers of data points in the range image with the polygons (defined by boundary vertices) that represent planar regions, which results in high data compression. In addition, polygons extracted from range image can be rendered in computer graphics tools faster than 3D point clouds with the aid of Graphical Processing Units (GPUs). These two aspects become prominent while rendering large number of fused range maps. The polygons are extracted as features as a preliminary step to build 3D range maps. Most recently, a number of researchers have worked on registration of multiple range images with polygons as features [4,8,9]. These approaches have been experimentally shown to be much faster than iterative point-based 3D registration techniques [1,10].

1.2. Related work

Planar segmentation is a widely studied topic in computer graphics, photogrammetry and robotics catering to numerous applications. Many algorithms have been developed in the field of computer graphics to obtain polygonal models of 3D point clouds for graphical rendering/visualization [11,12]. These algorithms are designed to model the objects with complex surfaces resulting in large number of polygons. The polygonal mesh can be further decimated or simplified by approximation based on the requirements to satisfy a certain level of detail for visualization as in [13,14]. We can identify two major steps in these approaches: mesh formation/triangulation and mesh approximation. The best known time complexity of mesh formation using Delaunay triangulation is $O(n \cdot \log n)$ for an unstructured 3D point cloud using divide-and-conquer strategy [15]. Further, [14] present an iterative process for mesh optimization and is based on minimization of a cost function. [13] employs constructing an error quadric metric that involves computing the plane parameters for each triangle in the mesh. These algorithms focus more on visualization with polygonal models and do not address real-time processing of range images.

The requirements for 3D mapping in robotics community are different from a computer graphics perspective. The latter focuses on building complex and accurate models of architectural objects at the expense of speed of the algorithms. The range scanners used in the field of computer graphics produce dense and highly accurate range images. The former focuses on building simpler 3D models using less accurate range scanners while they minimize the computation time of the feature extraction algorithm to satisfy the real-time applications such as Simultaneous Localization and Mapping (SLAM). A number of methodologies developed for robotic applications are available to extract simplified polygon models from 3D range images [16–21]. The complexity of the planar model is simple yet efficient to be useful in ground robot navigation [5,22] and aerial robot navigation [23].

We compare our algorithm with two popular plane segmentation algorithms, one is point-wise Region Growing (RG) algorithm and the other is RANSAC-based plane segmentation algorithm. An example of a RG algorithm to extract polygons from range data is presented in [17]. The planar segments are extracted from the range image in two steps. First, nearest neighbors are searched to identify coplanar data points belonging to individual planes. Second, the boundary points of each cluster are extracted to form polygons. The RG algorithm has a time complexity of $O(n^2)$, where n is the number of coordinate points in the range image. [20] is an extension of the work carried out in [17], where the authors of [20] modified the RG algorithm and reformulated the underlying mathematics to present an incremental version of planar segmentation. This improved the efficiency of the RG algorithm, which is described as follows. Initially, a random point (seed) and its nearest point is chosen as part of the set (Π)/region. More nearest points are added to the set (Π) in increasing distance from the set. This region is expanded by adding a nearest point p' if the point lies within a certain distance and satisfies the optimal planarity conditions defined in [20]. In addition, the authors explain the efficient implementation of the RG algorithm, which uses a priority queue and grid-based range images that implicitly store nearest neighbor information. Another optimization is presented for optimal plane calculation, which performs incremental update of attributes while storing previous calculations. This efficient version of the RG algorithm has a time complexity of $O(n \cdot \log n)$ [20]. Another example of plane segmentation algorithm that uses point-wise RG methodology is presented in [24]. The algorithm segments the range images into planar, smooth non-planar and non-smooth surfaces. The normal vectors are computed for each data point from a set of data points belonging to the local neighborhood. The RG algorithms in [17,20,24] are empirically fine-tuned with a set of parameters to segment planar regions within a tolerance limit. The RG methodology is not robust to noisy range images, which makes it difficult to fine-tune the parameters to segment range images with higher noise levels. Plane segmentation of noisy range images with RG algorithm may lead to incorrect segmentation, where one plane cluster fills partly into another plane cluster. The former plane cluster will blend into its neighboring plane leading to over-segmentation (additional points are added to the former plane segment that in real belongs to the latter plane segment) and the latter plane will undergo under-segmentation. The major drawback of the RG algorithm is that it is computationally slow. The normal vector is repeatedly computed for the set $(\Pi \cup p')$ while each data point (p') is tested for coplanarity with the optimal plane, which is an evaluation of data points to be included in a cluster. The normal vector computation for each data point is redundant and performed repeatedly on the covariance matrix of the data points. A well-known approach of extracting the normal vectors for a given set of data points is by solving the Eigen problem [25] for the covariance matrix of data points belong to the cluster, with a lower bound of $\Omega(n^3)$, where $(n = 3)$ is the size of the matrix. This repeated normal vector calculation is the reason why the RG algorithm is computationally slow in nature.

In addition, we compare our algorithm with another popular form of planar segmentation, which belongs to the class of model fitting using RANdom SAmple Consensus (RANSAC) [26]. Some recent efforts on planar segmentation from range data using RANSAC is presented in [27–29]. In general, a small number of data points are randomly chosen to establish the "hypothesis" set. The parameters of the planar model are computed from this minimal set of random points. Further, the "verification" step involves testing the remaining data points to see if it fits the model defined by the parameters computed earlier. If the error function evaluates to a value below a set threshold, then the data points are added to the "consensus set". The RANSAC plane segmentation algorithm stops looking for a better planar model once the probability of finding a better ranked consensus set drops below a certain threshold. The number of trials can be set heuristically as an