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Refinement of LiDAR point clouds using a super voxel based approach

Minglei Li [a,*], Changming Sun [b]

[a] College of Electronic and Information Engineering, Nanjing University of Aeronautics and Astronautics, China
[b] CSIRO Data61, Sydney, Australia

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ABSTRACT

We propose a new approach for automatic refinement of unorganized point clouds captured by LiDAR scanning systems. Given a point cloud, our method first abstracts the input data into super voxels via over segmentations, and then builds a K-nearest neighbor graph on these voxel nodes. Abstracting into voxel representation provides a means to generate an elastic wireframe over the original data. An iterative resampling method is then introduced to project resampling points to all potential surfaces considering repulsion constraints from both interior and exterior of voxels. Our point consolidation process contributes to accurate normal estimation, uniform point distribution, and sufficient sampling density. Experiments and comparisons have demonstrated that the proposed method is effective on point clouds from a variety of datasets.

1. Introduction

Vehicle-borne and aerial-borne laser scanning systems can obtain 3D point data of urban scenes with high efficiency and reliability. They usually combine light detection and ranging (LiDAR) modules with location and orientation sensors such as a GPS and an inertial measurement unit (IMU) onto the platform. These point clouds of urban scenes have significant values for various applications, such as urban modeling, vehicle navigation, environmental assessment, and virtual reality (Berger et al., 2014; Musialski et al., 2013; Rottensteiner et al., 2014).

Typically the raw data points from LiDAR scans or other sources often exhibit unorganized stripe structures due to the rotary scanning mechanism. These stripe structures make the point clouds to be lacking the inherent scene structures and to be difficult in estimating any orientation information. Oriented normal vectors on these points play a critical role in object recognition and surface reconstruction, because they provide the information on local surfaces and help identify the inside/outside of the underlying shapes (Alexa et al., 2003; Hoppe et al., 1992). Besides, any non-uniform densities of point clouds will seriously hinder local feature extraction. That is because most feature extraction algorithms depend on the statistical properties of points in a local region, while non-uniform densities make it difficult to define suitable neighborhood parameters over all scenes. Since LiDAR point clouds are unstructured and often massive, improving the distribution quality of these point clouds is becoming urgent.

The main focus of our work is on the development of a new method to consolidate point cloud data while preserving geometric precision. The assumption of our approach is that the point clouds collected by LiDAR systems maintain the same frameworks of the scenes, even though noise, outliers, and non-uniformities exist. The algorithm consists of two main parts: extracting a reliable elastic wireframe and resampling all points by optimal filling-in in the wireframe. And the algorithm is designed by conforming two principles. First, the topological structure of the whole scene is unchanged during the resampling process. Second, the resampled points fill the wireframe uniformly to make it well covered.

The main contribution of this work is the following. We present a generic technique that combines both data clustering and resampling to improve the quality of the scanned 3D points. Moreover, the resampling method is designed based on an elastic wireframe and a geometric criterion derived from the statistical information of super voxels, which significantly improve the computation efficiency. In general, the proposed algorithm can lead to uniform distribution of data points and improve the quality of surface normal estimation.

2. Related work

In the field of point cloud processing, surface modeling and semantic segmentation have been extensively researched (Berger et al., 2014; Vosselman et al., 2017) compared with the deficiency

* Corresponding author.
E-mail addresses: minglei_li@126.com (M. Li), changming.sun@csiro.au (C. Sun).

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of point cloud consolidation. Due to the rapidly growing demand in different applications of using LiDAR point clouds, the work on quality refinement of point cloud data has been seen in increasing usages.

In order to improve the quality of aerial LiDAR point clouds, much efforts have been spent in dealing with horizontal and vertical offsets of overlapping adjacent LiDAR strips, where the offsets are caused by undetected systematic errors. The emphasis in this case was on the extraction of the shapes of building roofs (Rentsch and Krzystek, 2009). Relative offsets between overlapping areas of adjacent strips are measured by the detection and comparison of reconstructed roof ridge lines. By introducing the offset measurements as observations, the residual errors for offsets and rotations are resolved by bundle adjustment approaches (Habib et al., 2008; Vosselman, 2008). To deal with multiple registered scans, many improvement methods on the iterative closest point algorithms have been developed for iteratively estimating the transformation parameters from geometric feature correspondences (Gressin et al., 2013; Yang et al., 2015). However, rigid point cloud models from different scans will exhibit inevitable gaps and non-uniform densities after registration, which may be caused by system errors or movement of the scene. A further refinement process on the registered data is necessary.

In most of the point denoising algorithms, point sets are smoothed according to local surface features. Deschaud and Goulette (2010) use surfaces obtained by moving least squares (Alexa et al., 2003) to describe the local geometry by extending a 2D non-local denoising method (Buades and Morel, 2005). Morales et al. (2010) present a semi-rigid grid decimation method on point clouds, which achieves a superior time performance compared with those of surface denoising methods. Benhabiles et al. (2013) attempt to simplify the entire input dataset while preserving sharp edges based on dividing the data into a 3D grid of clusters, approximating the local shape of objects in each cluster and removing points located far from those shapes. Denoising is a typical way for refining the quality of point clouds while not changing the unstructured characteristics of the original data points.

In the community of computer graphics, there are algorithms for the refinement of point set surfaces depending on local geometry analysis such as curvature estimation (Lange and Polthier, 2005). Lipman et al. (2007) develop a highly effective, parameterization-free locally optimal projection (LOP) to deal with outliers. However, LOP may not work well when the distribution of the input data points is highly non-uniform. Huang et al. (2009) modify and extend LOP by incorporating locally adaptive density weights on LOP as WLOP to deal with non-uniform distributions which are common in raw data. When handling large scale data, WLOP will face the low efficiency problem.

Most implicit surface modeling methods assume that surfaces represent an isosurface over the observation objects, and all vertexes of the reconstructed surfaces are a new point set derived from the original point cloud via tangent plane estimates (Hoppe et al., 1992), radial basis function (RBF) (Carr et al., 2001), or Poisson fields (Kazhdan and Hoppe, 2013). Basically, these methods use a smoothing procedure on a raw point cloud, and a prior estimation of normal vectors over all points is essential. Delaunay triangulation based surface modeling methods are explicit, and they typically produce meshes interpolating the input points neglecting noises and outliers (Cazals and Giesen, 2006). Besides, in order to compensate the data quality defects, many urban modeling methods use various a priori knowledge such as Manhattan assumption (Li et al., 2016) and pattern symmetry and repetition (Nan et al., 2015). The aforementioned methods require that the input data satisfy certain preconditions, and this hinders their capabilities on general scenes.

3. Proposed method

The proposed algorithm consists of two main stages, as shown in Fig. 1. The first stage is to abstract the point clouds with a subset using an adaptive octree algorithm so that flexible supporting points can be computed based on octree nodes. Based on these supporting points, region growing based over segmentation is implemented to generate super voxels, which are regarded as abstracted nodes and are to be used to further generate a K-nearest neighbor (KNN) graph as an elastic wireframe. In the second stage, the super voxel based wireframe is used to constrain the resampling process. The resampling points are inserted in the grids of the wireframe and adjusted to be projected on the scene surface along the normal direction. Then the distributions of all inserted points are refined based on an energy function that enables a uniform point distribution. The super voxel based graph works like a sieve to assign the distributions of the resampled points when they are stretched out and pushed back using a fixed iteration method.

3.1. The establishment of super voxel based wireframe

The flexible and elastic wireframe is built based on super voxels which are treated as grid nodes. Super voxels are the result of an over segmentation process that clusters locally consistent points into many patches. Our over segmentation method is designed as an adaptation of the region growing method which is widely used for segmentation because it is easy to implement. The selection of seeds and the criteria for growing are critical in these processes. In order to obtain consistent segments, many methods tend to select points in the interior of flat regions as seed points. For instance, Vieira and Shimada (2005) and Nurunnabi et al. (2012) removed points along sharp edges using a curvature threshold and the remaining points were considered as seed points. However, this strategy will lose the applicability for some protruding structures, such as streetlights and fire hydrants in a large scene. To overcome

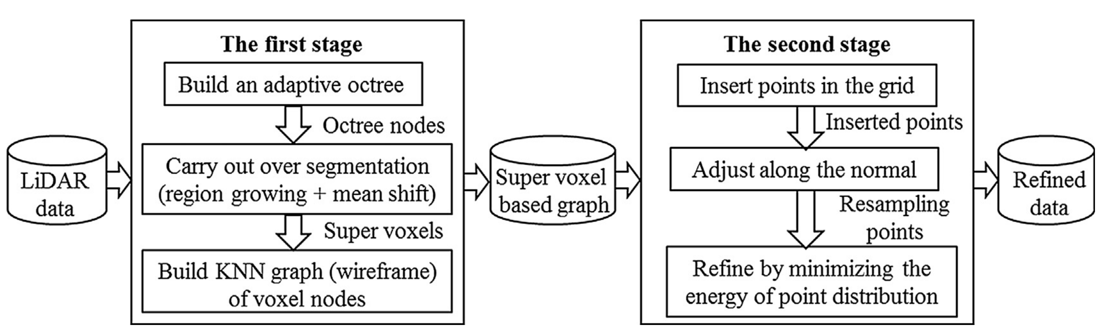

Fig. 1. Flowchart of the proposed approach.

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