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Surface Reconstruction for Ground Map Generation in Autonomous Excavation †

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Abstract: Excavator's main tasks include digging, trenching, and ground leveling at construction sites, as well as work efficiency and safety can be improved by using an autonomous excavator. A prerequisite step to achieving an autonomous excavation is to obtain a sound perception of the surrounding ground. For this, a LiDAR sensor has been widely used to scan the environment. However, the point cloud generated by the LiDAR is not ideal for surface reconstruction to generate a ground map, as it suffers from flaws such as noise and outlier points. To tackle this issue, our paper proposes advanced methodologies for surface reconstruction algorithms.

Keywords: autonomous excavation; surface reconstruction; LiDAR; curve approximation

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1. Introduction

An autonomous excavator requires perception about its surrounding environment. For various excavation tasks, a LiDAR sensor can be used to scan the surface at digging sites and to generate a corresponding ground map in a point cloud format. However, surface reconstruction is a challenging task and its difficulty varies depending on the distribution of points. In particular, surface reconstruction with scatter data is more challenging [1] and most methods fail to converge to a hole-free and complete surface. As an example of the existing approaches in surface reconstruction, the proposed algorithms in [2,3] require knowledge about the connectivity of unordered points in space. The authors in [4,5] provided neural network-based approaches to optimize the reconstructed surface. As an alternative solution, the optimization method needs significant computing power, and is therefore not suitable for semi-real-time applications such as autonomous excavators. The rest of this paper describes the design of the proposed novel method for surface reconstruction, along with validation results and concluding remarks.

2. Point Cloud Enhancement

In this paper, a Velodyne Puck (VLP-16) LiDAR with 16 laser channels was used to obtain point cloud data from the targeted surroundings (ground). The LiDAR sensor fires lasers sequentially through channels and reports the obstacle's distance from its center. Depending on the objects in the environment, each laser firing may produce multiple reflections. The selected LiDAR has two options: 'Last' and 'Strongest'. In the Last option, the distance with the farthest reflection of the laser beam is reported, while the Strongest option reports the distance with the highest intensity reflection. This study chose the Last option because the digging ground is always the last visible object in the environment and the Strongest option may allow the light to return from particles or dust in the environment rather than from the ground.

2.1. Coordinate Systems

The LiDAR sensor reports the points in polar coordinates. The azimuth for this coordinate can be defined by the sensor's encoder at the start of a firing sequence. The elevation is predefined by the manufacturer and depends on the laser channel's number. Finally, the distance is the same as that measured by the sensor. Data points in polar coordinates can be translated into Cartesian coordinates using equations provided by the manufacturer. We investigated which coordinate system fits better for the surface reconstruction as follows.

2.1.1. Cartesian Coordinates

At the first glance, mapping point cloud data and applying surface reconstruction methods in x, y, and z Cartesian coordinates may seem convenient and yield proper results because Cartesian coordinates are more intuitive. A major limitation of Cartesian coordinates is that their data points are likely to be unordered. Specifically, there is no relationship or sequence between individual data points. Thus, the method of surface reconstruction must attempt to connect scattered points in the space to form a surface.

Some approaches and strategies for this purpose require prerequisites such as denoising, normal vectors, and non-uniformity and outliers [6]. However, they are mainly unavailable while using LiDAR sensors. Thus, a completely closed surface is not guaranteed.

2.1.2. Polar Coordinates

Processing data in polar coordinates has the main advantage that data points can be arranged in an evenly distributed pattern, ensuring the generation of a valid and hole-free surface. Thus, polar coordinates were chosen for surface reconstruction using the following curve approximation method.

3. Curve Approximation Method

The LiDAR sensor senses and reports a series of paired azimuth and distance data for each elevation angle. As shown in Figure 1, the distance data may contain noises and outliers. So, the initial step for surface reconstruction is to apply a curve approximation to retain the shape of the ground while discarding the noises and outliers. Additionally, having an analytical equation rather than a series of data helps in evaluating the ground shape at any azimuth angle rather than relying solely on the azimuth data reported by the LiDAR sensor. To evaluate the performance of the proposed method, tests were carried out on an inclined plane with two bumps.

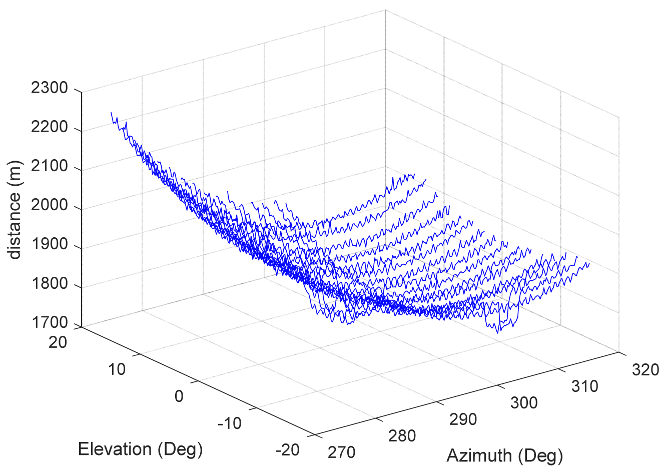

Figure 1. Representation of point cloud in polar coordinates.

In this paper, the cubic Bezier curve was applied to approximate the surface curves. The cubic Bezier curve has 4 control points as seen in Equation (1) where the control points of $\boldsymbol{P}_0$ and $\boldsymbol{P}_3$ match exactly the initial and final data points. Thus, the optimization process adjusts only the x and y positions of $\boldsymbol{P}_1$ and $\boldsymbol{P}_2$ control points to reduce the absolute error between the actual data set and the approximated curve.

$$\boldsymbol{B}(t) = (1-t)^3\boldsymbol{P}_0 + 3(1-t)^2 t\boldsymbol{P}_1 + 3(1-t)t^2\boldsymbol{P_2} + t^3\boldsymbol{P_3} \qquad 0 \le t \le 1 \tag{1}$$

$$\boldsymbol{P}_i = \{P_{ix}, P_{iy}\} \qquad i = 0, 1, 2, 3 \tag{2}$$

where $\boldsymbol{B}(t)$ is the Bezier curve. t is the progress. $\boldsymbol{P}_i$ represents the ith control point. P_{ix} and P_{iy} are the x and y position of the ith control point.

Each laser channel has an associated fixed elevation degree. Thus, each of the 16 laser channels can be displayed by a series of azimuth and distance pairs. The cubic Bezier curve approximation can be applied to distance data based on azimuth. Figure 2 shows the approximated cubic Bezier curve on four different laser channels.

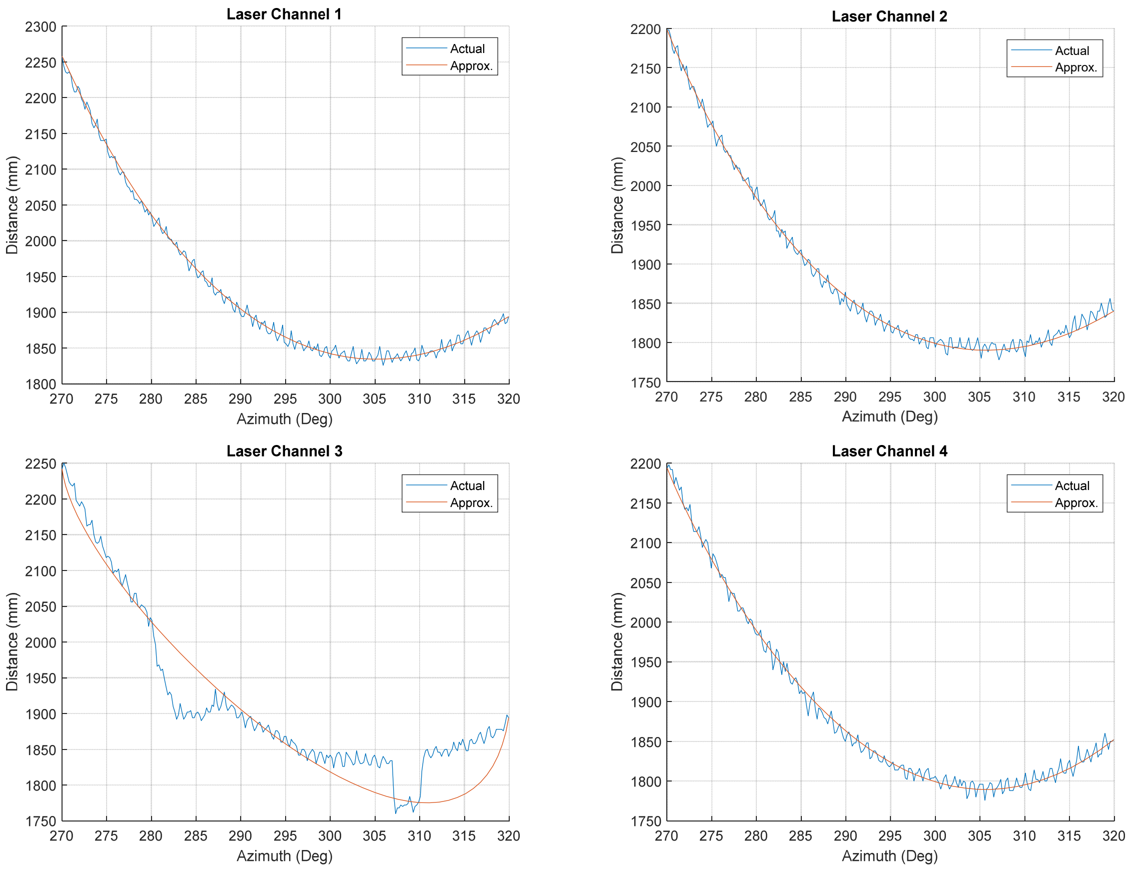

Figure 2. Curve approximation on raw data sets.

4. Surface Reconstruction

Following the approximation of a single curve for each laser channel, the next step is to stitch the individual approximated curves together to make a single map. For this, a linear interpolation between neighbor curves was used. A series of points in polar coordinates were evaluated from the approximated surface, and then they were converted into Cartesian coordinates to generate the actual ground shape in Cartesian space.

Figure 3 illustrates the result of surface reconstruction in polar coordinates using the raw and noisy data of laser channels in Figure 2 after applying the above steps.

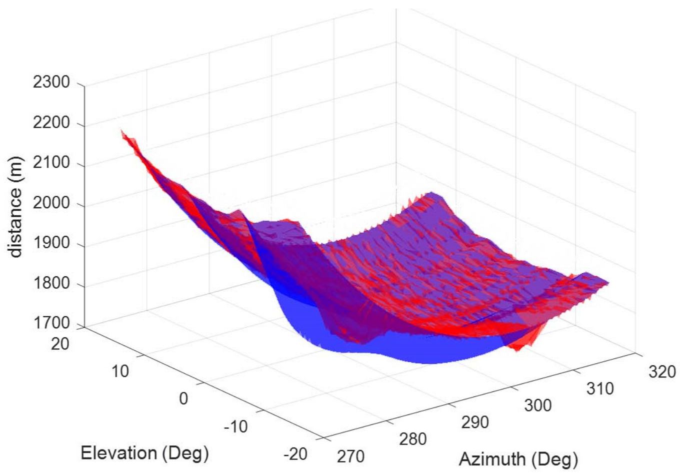

Figure 3. Result of surface reconstruction in polar coordinates: raw data (red) and approximated curves (blue).

5. Result

Figure 4a shows the result of converting the raw data points that were reported by the LiDAR, from polar coordinates to Cartesian coordinates. Figure 4b represents the approximated surface in Cartesian space that is converted from Figure 3.

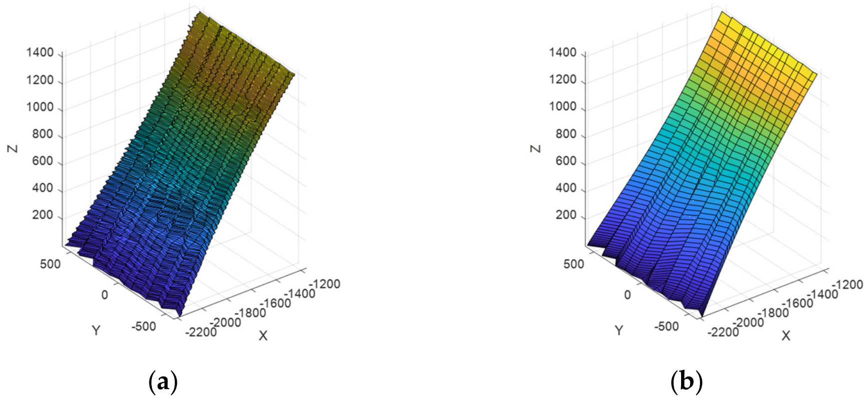

Figure 4. Result of surface reconstruction in Cartesian coordinates: (**a**) Raw (original) point cloud (**b**) Reconstructed surface.

The maximum deviation of the approximated curve from the original surface is about 22 cm. In addition, the total required time for surface reconstruction is about 0.5 s.

6. Conclusions

The study proposes a curve approximation-based method to reconstruct the surface of digging ground using data sets from a LiDAR sensor. A key feature of this method is to offer the benefit of overcoming the problem of data point disorder in Cartesian coordinates and reducing computation time, which enables autonomous excavators to identify dynamic changes in the environment.

Therefore, implementing the proposed surface reconstruction methods in the excavation application will allow for better identification of the ground shape and provide a solid foundation for the generation of optimal trajectory and accurate tracking control that are required for completing a successful autonomous excavation.

For further development, the proposed method can be applied to improve excavation safety by detecting obstacles in digging areas, and therefore helping in the design of controllers to avoid collisions with existing underground infrastructure. Another safety application of our method is to monitor the effects of deep excavation on seismic vulnerability of existing facilities [7] and groundwater leakage-related hazards [8].

Finally, the proposed approach works only with static objects. Hence, its extension to detect, segment, and identify dynamic objects on the static ground will also contribute to enhancing the safety of excavation operations.

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