Title:
Segmentation of Large-Scale Anisotropic Point-Clouds Captured by Mobile Mapping Systems

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Introduction:

A mobile mapping system is an equipment on which as laser scanners, cameras, GPSs, and an IMU are mounted, as shown in Fig. 1. The MMS can acquire point-clouds of roads, buildings, traffic signs, utility poles, trees, and so on while the vehicle moves. In recent years, the performance of the laser scanner has been greatly improved, and it can measure from 300,000 to 1 million points per second. When point-clouds are captured for several hours with an MMS equipped with a high-performance laser scanner, billions of points can be obtained.

In order to create 3D models from huge point-clouds, it is necessary to efficiently estimate adjacency relationships among points and evaluate connectivity of the neighbor points. However, points captured using the MMS are highly anisotropic, as shown in Fig. 2. While points are dense in the scanning directions, they are relatively sparse in the traveling direction. When a vehicle equipped with a laser scanner moves forward, the laser beam is spirally irradiated, as shown in Fig. 2(a). When the vehicle moves at 40km/h with the laser scanner shown in Fig. 1(c), point intervals differs by 10 times or more between the irradiation direction of the laser and the traveling direction of the vehicle.

This problem makes it difficult to robustly evaluate connectivity of neighbor points. For example, neighbor points are typically detected using a sphere or the k-closest search, but these methods do not work well for anisotropic points.

In this paper, we propose a new method for estimating local connectivity of points for anisotropic points captured using the MMS. Most existing methods process point-clouds only using coordinates, we utilize the fact that the surveyor knows measurement conditions. Such additional data include useful

Fig. 1: Mobile mapping system: (a) Vehicle with an MMS, (b) Close-up of MMS, (c) Laser scanner.

information for robustly evaluating connectivity among points. First, we present that neighborhood can be robustly detected using the GPS time of each point and parameters of the laser scanner. Then we also present that the laser beam for each point can be simulated using the trajectory data. Then, the distance from each neighbor point can be estimated using simulated laser beams if neighbor points are on the same continuous plane. In our method, the connectivity is estimated by comparing the measured distance with the estimated distance. We note that our method is complementary to existing segmentation methods, such as region growing and RANSAC methods. Our method allows region growing to quickly and robustly obtain adjacent and connected points. For RANSAC methods, our method can be used to restrict search areas by recursively extracting continuous surfaces.

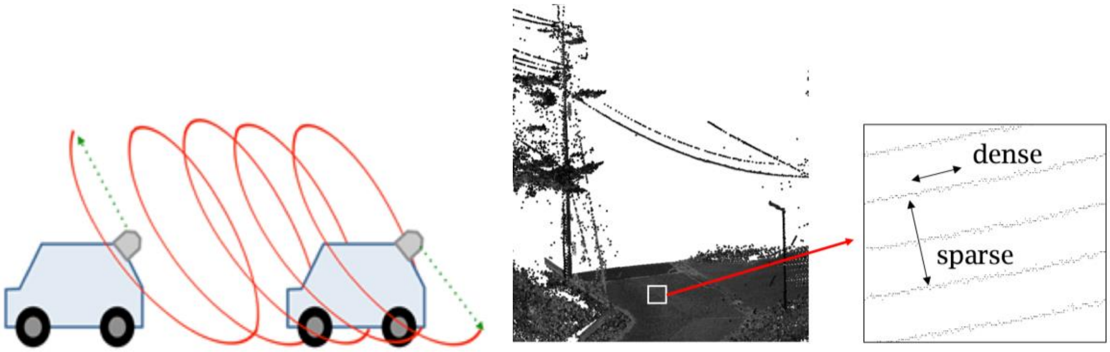

Fig. 2: Anisotropic point-clouds captured by an MMS: (a) Trajectory of laser beams, (b) Anisotropic intervals of points.

Mapping Points onto 2D Lattice:

To detect adjacency relationships among points, we project point-clouds onto the 2D lattice using GPS time and the parameters of laser scanners [1], [2].

We suppose that each point in point-clouds has a coordinate and the GPS time, and the trajectory of the scanner positions are given. We also suppose that the rotation frequency and the pulse reputation frequency of the laser scanner are given. The pulse reputation frequency indicates the number of measurements per second. Let f be the rotation frequency, and ω be the pulse reputation frequency. When the rotation frequency f is constant, the laser beam rotates once every $1/f$ second. Therefore, the adjacent scan-line includes points measured $1/f$ second later, as shown in Fig. 3.

In order to map point-clouds onto the 2D lattice, the phase number and rotation number are assigned to each point, as shown in Fig. 4. The phase number indicates the order of the points on each scan-line, and the rotation number represents how many times the laser beams has rotated since the start of measurement.

Let t be the elapsed time from the start of the measurement until the point $\mathbf{P}$ was measured. Then the phase number I and the rotation number J can be calculated using the following equations.

$$I = int\,(\omega \cdot fmod\,(\,t, 1/f)) \tag{2.1}$$

$$J = int\,(\omega \cdot t) \tag{2.2}$$

By mapping each point to (I, J), point-clouds are converted to the 2D lattice, as shown in Fig. 4.

The normal direction of each point can be estimated by fitting a plane to neighbor points. We define the neighborhood on both image space and 3D space. To detect neighbor points of point $\mathbf{p}_{i,j}$, firstly, we select points in a circle with radius r_2 on 2D lattice. Although point intervals in 3D space are largely different in the I and J directions, the nearly same number of points are selected in the both directions. Then we eliminate points outside the sphere with radius r_3 in 3D space. The normal vector is estimated for each point by using selected neighbor points. We denote the normal vector of $\mathbf{p}_{i,j}$ as $\mathbf{n}_{i,j}$.

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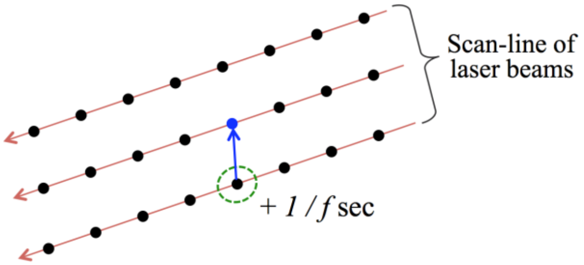

Fig. 3: The nearest point adjacent scan-line.

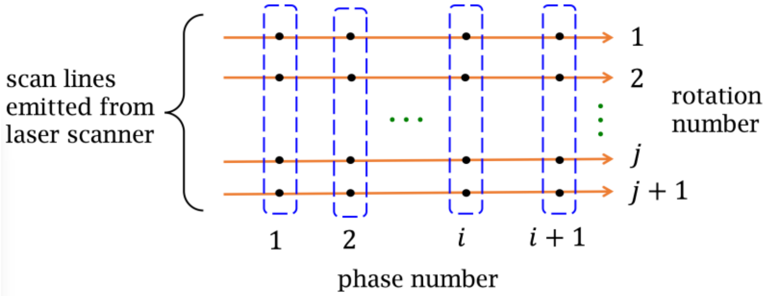

Fig. 4: The phase number and the rotation number.

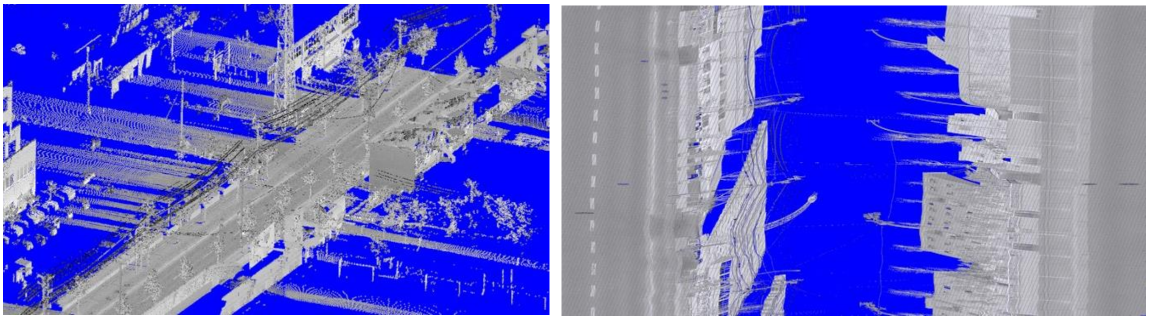

Fig. 5: Mapping onto the 2D lattice: (a) Point-clouds, (b) Points on the 2D lattice.

<u>Segmentation of Points:</u>

The data size of the point cloud captured using MMS is too large to be loaded into PC memory. Therefore, it is necessary to divide the data for point processing. In Fig. 6(b)., points loaded at one time are shown in different colors. Since roads on which the vehicle runs are very large continuous regions, roads are firstly detected and separated from point-clouds. In our case, it is trivial to detect roads, because the trajectory of the vehicle is given and it is known that the roads exists directly under the vehicle.

By eliminating points on roads, objects such as buildings and utility poles on the road can be separated into relatively small continuous regions. However, since points are highly anisotropic, thresholds for connectivity have to be adaptively determined.

We assign the scanner position to each point. Here, we denote a point-cloud as $\{\mathbf{p}_{i,j}\}$ and $\{t_{i,j}\}$, where $\mathbf{p}_{i,j}$ is a 3D coordinate mapped at (i,j) on a point image, and $t_{i,j}$ is the GPS time. We also denote the scanner position as $\mathbf{s}_{i,j}$. In typical MMS systems, the trajectory of the scanner positions are given as 3D coordinates $\{\mathbf{q}_k\}$ with GPS times $\{u_k\}$. To calculate the scanner position $\mathbf{s}_{i,j}$ for point $\mathbf{p}_{i,j}$, we detect the following index k.

$$u_k \le t_{i,j} < u_{k+1} \tag{3.1}$$

Then the scanner position $\mathbf{s}_{i,j}$ is calculated as:

$$\mathbf{s}_{i,j} \equiv \mathbf{s}(t_{i,j}) = \frac{(u_{k+1} - t_{i,j})\mathbf{q}_k + (t_{i,j} - u_k)\mathbf{q}_{k+1}}{u_{k+1} - u_k} \tag{3.2}$$

We estimate the rotation axis of the laser beam by using the Gauss map of vectors $\mathbf{p}_{i,j} - \mathbf{s}_{i,j}$. We project points on scan-line j on a unit sphere, and fit a plane to the projected points. The normal vector of the plane is parallel to the rotation axis of the laser scanner. We denote the rotation axis of scan-line j as $\mathbf{a}_j$, and the rotation matrix around the axis $\mathbf{a}_j$ as $\mathbf{R}_\mathrm{j}(\theta)$.

Then we consider whether neighbor points $\mathbf{p}_{i,j}$ and $\mathbf{p}_{i+k,j+l}$ are on the same continuous surface. First, we estimate the equation of the laser beam for $\mathbf{p}_{i+k,j+l}$ [3]. Since the rotation angle between the two points are $2\pi k/\omega$, the laser beam direction for $\mathbf{p}_{i+k,j+l}$ can be estimated as:

$$\mathbf{R}_\mathrm{j}\left(\frac{2\pi k}{\omega}\right)(\mathbf{p}_{i,j} - \boldsymbol{s}_{i,j}) \tag{3.3}$$

We denote that the normalized direction as $\bar{\mathbf{v}}_{i+k,j+l}$. The estimated laser beam is calculated as a straight line with the direction $\bar{\mathbf{v}}_{i+k,j+l}$ through the scanner position $\mathbf{s}_{i+k,j+l}$.

We suppose that $\mathbf{p}_{i,j}$ and $\mathbf{p}_{i+k,j+l}$ are on the same plane whose normal vector is $(\mathbf{n}_{i,j} + \mathbf{n}_{i+k,j+l})/2$. Then the position of $\mathbf{p}_{i+k,j+l}$ can be estimated as the intersection point between the plane and the estimated laser beam, as shown in Fig. 7. We denote the estimated position as $\bar{\mathbf{p}}_{i+k,j+l}$.

If the assumption that the two points are on the same plane is correct, the distance $|\mathbf{p}_{i,j} - \mathbf{p}_{i+k,j+l}|$ becomes nearly equal to the distance $|\mathbf{p}_{i,j} - \bar{\mathbf{p}}_{i+k,j+l}|$. Therefore, we estimate that $\mathbf{p}_{i,j}$ and $\mathbf{p}_{i+k,j+l}$ on the same surface if the following condition is satisfied. λ is a constant greater than 1.

$$|\mathbf{p}_{i,j} - \mathbf{p}_{i+k,j+l}| < \lambda|\mathbf{p}_{i,j} - \bar{\mathbf{p}}_{i+k,j+l}| \tag{3.4}$$

In our method, mesh models can be generated by connecting neighbor points on the 2D lattice. However, point-clouds captured using the MMS are very noisy and have a lot of missing points. Therefore, we apply the Delaunay triangulation on the 2D lattice to detect adjacency relationships. Then, the two points of each triangle are connected if they satisfy the condition Eqn. (3.4).

(a) A part of point-clouds

(b) Loading of point-clouds

(c) Height of roads

(d) Detection of points on roads

Fig. 6: Separation of road.

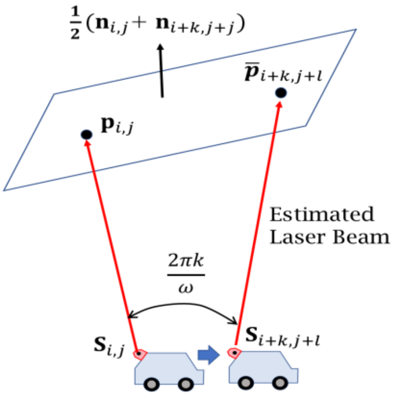

Fig. 7: Estimation of the neighbor position.

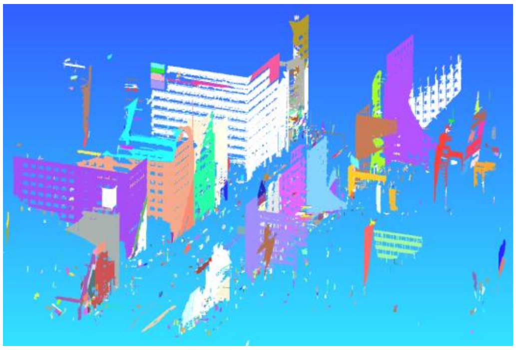

Fig. 8: Extraction of continuous regions.

Surface Extraction:

In Fig. 8 detected continuous regions are shown in different colors. By using our method, continuous regions can be stably detected from large-scale anisotropic point-clouds. Since each segmented surface is relatively small, it can be further segmented efficiently by applying region growing or RANSAC methods. In Fig. 9., a continuous surface is subdivided into planar regions using the RANSAC method.

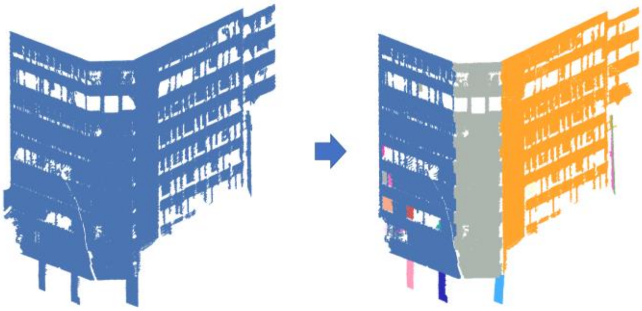

Fig. 9: Segmentation into planar regions.

Conclusion:

In this paper, we proposed a method for segmenting large-scale anisotropic points into relatively small continuous surfaces. For efficiently processing points, we mapped points onto a 2D lattice using GPS times and scanner parameters. For connecting points on the 2D lattice, we introduced adaptive thresholds, which are determined using scanner positions, the trajectory of the vehicle, and scanner parameters. By using adaptive thresholds, the connectivity of points could be stably evaluated.

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