

Objective Evaluation of Scanning Ladar Configurations for Mobile Robots

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Abstract — Scanning laser range sensors (ladars) are frequently used in mobile robotics applications because their ability to accurately measure the environment in 3D makes them well-suited for perception tasks like terrain modeling and obstacle detection. The choice of ladar sensor and the manner in which it is configured and integrated into a robot platform is usually determined subjectively based on the experience of the project team members. This paper develops a method for evaluating ladar sensors and sensor configurations that objectively measures the quality of a sensor/configuration choice in terms of density and uniformity of measurements within a region of interest. The method is applicable to static sensors and environments as well as scenarios with moving objects and mobile sensors. It can be used to compare different sensors, to evaluate specific sensor configurations and search for the optimal one, and to aid in designing new ladar sensors tailored to specific applications. We find that popular ladar configurations are often not the best configuration choice, and that alternative configurations not commonly used would offer better data density and uniformity.

I. INTRODUCTION

Scanning laser range sensors (ladars) are frequently used in mobile robotics applications [1-7]. Ladars provide accurate 3D measurements of a robot's environment, which makes them well-suited for key perception tasks, such as terrain modeling and obstacle detection. Different ladars have different properties (e.g., sampling rate, field of view, angular increment, etc.), and ladar sensors can be mounted and actuated in a variety of ways. Any project that uses ladar sensors for perception must make decisions as to which sensor is to be used and how it is to be configured during integration. In many projects, these decisions are made in a subjective manner based on the experience of the project team members.

This paper presents a method to objectively answer the questions "Which ladar sensor is the best choice for a given application?" and "How should a given ladar sensor be mounted and configured to optimize perception performance?" Intuitively, since ladars typically operate at a fixed sampling rate, a ladar configuration that concentrates

points in the region of interest for a given application will be better than one that spreads points uniformly throughout the environment. For example, if the goal is to model the terrain for path planning, a configuration in which a large percentage of the points are uselessly measuring the distance to the sky is not as good as one that focuses most of the points on the ground in front of the robot.

Our approach to the problem is to simulate different ladar configurations and to define an objective measure of data quality that can be computed for a given configuration (Fig. 1). Armed with an objective data quality measure, it is possible to compare different ladar sensors to determine which is better, to search for the optimal configuration for a given sensor, or to evaluate hypothetical ladar sensor designs for customizing a sensor for a particular application.

Our approach focuses on the perception aspects of the question of ladar quality. We do not consider other factors unrelated to perception that go into making a decision on sensor choice or configuration. Some of these factors include cost, complexity, ease of integration, ruggedness, and power usage. These factors could be included in a more complex evaluation metric by combining them with the perceptual configuration quality measure using appropriate weighting factors.

II. RELATED WORK

Early work by Kelly characterized scan patterns for horizontally and vertically nodding ladars analytically but did not try to objectively compare different configurations [8]. While analytical formulas for density are easy to evaluate and manipulate, Kelly's approach makes numerous assumptions that are not realistic for laser scanners, including assumptions that the data is measured instantaneously, that it is arranged uniformly on a rectangular grid, and that the laser footprint is the same size as the range image pixel size. Moreover, the approach does not have any obvious extension to more complex scanner configurations. More recently, Wulf and Wagner identified several additional practical configurations for line scanning ladars that are rotated using a servo [9]. The authors plotted scan patterns for these configurations and made subjective observations about which configuration was most useful for different robotics and 3D mapping applications. They observed – as have other researchers – that higher density of

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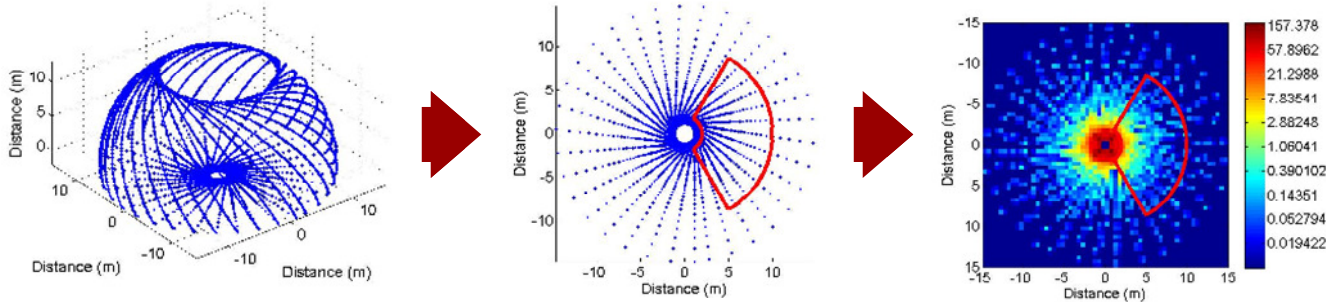


Fig. 1. Overview of our approach. Left: A lidar simulator is used to generate 3D rays. Center: The rays are intersected with surface models, such as the ground (as shown here) or object models to obtain a distribution of point measurements on the surface. Right: The point measurements are accumulated in a histogram (log scale), from which data density and uniformity within a region of interest can be evaluated to obtain summary statistics for comparing different lidar configurations. Here, the lidar is rotated around a vertical axis but is mounted with a 30 degree roll angle.

measurements can be obtained by pointing the rotation axis in the direction of interest [10]. This work, did not consider, the full space of configurations that we cover, nor did it include any objective measures to compare the different configurations. Other scan patterns are possible with specialized sensors. For example, Blais et al used a lissajous pattern to improve performance for real-time target tracking in 3D [11]. They found that lissajous patterns allow tracking speed that is several orders of magnitude faster than would be possible with a raster scanning pattern. This is an example of a scanning configuration that is optimized for a specific application. Similarly variation of configurations controlling the degree of data density have been studied with respect to the domain-specific application of forest canopy analysis using aerial lidar [12].

III. MODELING LADAR CONFIGURATIONS

Our approach for evaluating lidar configurations utilizes a lidar simulator to generate point measurements. This simulator needs to model the basic properties of a sensor, such as the sampling rate and the laser actuation mechanism and timing, but it is not necessary to model advanced properties like data uncertainty, mixed pixels, or precise laser spot size and shape.

Although a wide variety of lidar sensors are commercially available, a few technologies and laser actuation schemes have emerged as the predominant solutions within the mobile robotics domain. Among the range measurement technologies, pulsed time of flight (PTOF) is the dominant technology, though several amplitude modulated continuous waveform (AMCW) sensors are available, and flash lidar is a promising next generation technology. Our approach is general enough to handle any of these lidar technologies.

A lidar's actuation scheme determines the pattern of laser pointing directions over time. One popular approach is to use a spinning mirror or prism to redirect the laser in a radial pattern, resulting in a line scanning lidar (e.g., SICK LMS 200/291 and Hokuyo UTM-30LX). To achieve full 3D

sensing, a second type of actuation is needed. One solution is to use a servo to mechanically rotate the entire sensor head, either in a continuous rotation or a back-and-forth nodding motion. Such sensors are commercially available, but more frequently they are custom-designed [2-4, 6, 7, 10].

We focus our analysis on this rotating/nodding type of lidar system, since the design is popular in mobile robotics applications and presents an interesting array of configuration parameters that are difficult to manually optimize. It is straightforward to extend our approach to use a different lidar simulator in order to analyze other types of actuation mechanisms, such as that of the Velodyne HDL-64E S2, which was used in the Urban Grand Challenge [5].

For the rotating/nodding system, we establish three coordinate frames within the world coordinate system, all with the same origin located at the scanner center of projection, but with potentially different orientations (Fig. 2). We denote the axis of the spinning mirror/prism as the primary rotation axis, and the axis of the rotating/nodding sensor head as the secondary rotation axis. The world coordinate frame origin is located at an arbitrary point on the ground plane with the z axis pointing up with respect to gravity. The *platform coordinate frame* is affixed to the

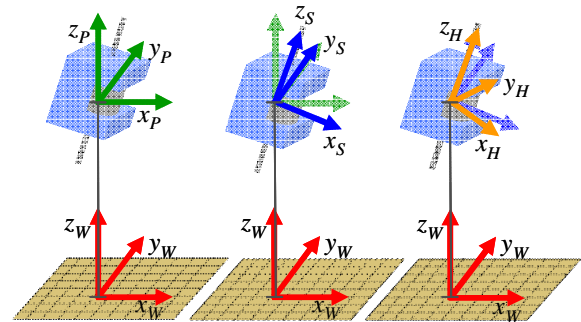


Fig. 2. We define three coordinate frames within the world coordinate system (W subscripts). The platform coordinate frame (P subscripts), which is attached to the vehicle platform, the scanner system coordinate frame (S subscripts), which is attached to the scanner, and the scanner head coordinate frame (H subscripts), which nods/rotates with the scan head.

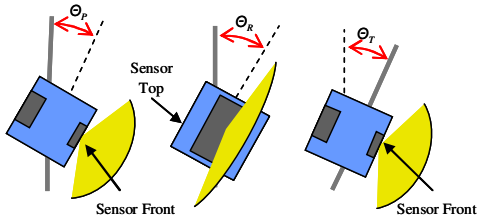


Fig. 3. The ladar sensor mounting configuration has three parameters – the pitch angle (θ_P), the roll angle (θ_R), and the tilt angle (θ_T). See text for details.

(potentially moving) platform, with its initial orientation the same as the world coordinate system. The platform is oriented so that the x-axis points in the robot’s forward direction and the y-axis points left. The *scanner system coordinate frame* is affixed to the ladar scanner with the z-axis coincident with the secondary rotation axis. The *scanner head coordinate frame* is affixed to the rotating/nodding portion of the scanner with the z-axis coincident with the primary rotation axis. Typically, the primary and secondary axes of the scanner are oriented orthogonally, but that is not required, and it is not necessarily the best configuration.

Parameters for a ladar system may be configurable, or they may be fixed by the choice of the device. The sampling rate is the number of 3D points that the sensor measures per second (r). The primary angular increment (Δ_P) is the angle between successive samples. The secondary angular increment (Δ_S) is the angle that the scanner head rotates during a single rotation of the spinning mirror. This parameter is governed by the angular rotation about the secondary rotation axis. The scanner can have limits on the field of view in the primary rotation plane (Φ_{line_min} , Φ_{line_max}), which are typically not configurable. Several parameters are associated with how the various coordinate frames are oriented with respect to one another (Fig. 3). The pitch angle of the line scan can be adjusted by rotating the ladar head with respect to the primary rotation axis (θ_P); the roll angle (θ_R) can be controlled by rotating the sensor around an axis perpendicular to the primary and secondary rotation axes; and the secondary rotation axis itself can be tilted with respect to vertical in the world coordinate frame (θ_T). Nodding sensors are modeled similarly to rotating sensors, except that two additional parameters are used to set the angles where the sensor reverses direction (Φ_{nod_min} , Φ_{nod_max}). Finally, the sensor itself can be mounted at a given height (h) above the ground.

IV. SURFACE MODELS AND REGIONS OF INTEREST

The ladar simulator generates rays emanating from the ladar, which intersect surfaces in the environment to produce point measurements. We consider three types of surface models: a ground surface model, a non-ground surface model, and an object model (Fig. 4). The ground

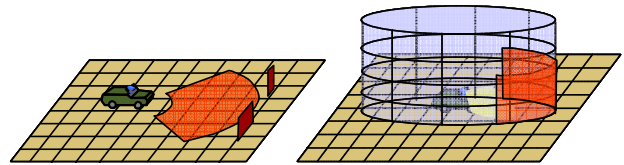


Fig. 4. The three types of surface models – ground (beige plane, left), non-ground (blue cylinder, right), and objects (red rectangles, left). The region of interest for ground and non-ground models is shown in orange.

surface model is used for analyzing the density and distribution of points on the ground and is useful, for example, in terrain modeling. The non-ground surface model is used for analyzing data distributions on surfaces above the ground, such as building walls in an indoor modeling application. The object model is used for analyzing specific objects that have typical sizes, such as cars or people, which would be important for an urban navigation application. Our ground surface model is simply an infinite horizontal planar surface. We model non-ground surfaces with a vertical cylindrical surface surrounding the sensor at a fixed radius R . The object model consists of a set of vertical rectangular planar surfaces, which can be placed at arbitrary locations and orientations in the environment. More complex surface models could be employed for advanced analysis within this framework. For example, an actual or simulated terrain surface could be used to analyze sensor configuration choices for different terrain shapes and slope characteristics.

Real sensors mounted on real platforms have limited fields of view due to self-occlusion (e.g., points that hit the vehicle itself) and sensing range limits. Also, depending on the application, a specific region may be of importance. For example, when driving forward, a terrain modeling algorithm is most interested in the region immediately in front of the vehicle.

To accommodate these considerations, a region of interest can be specified, and computations are then limited to this region. We specify regions of interest on the ground surface using polar coordinates to limit data to a minimum and maximum distance from the base of the sensor and a minimum and maximum azimuth angle in the vehicle coordinate frame (Fig. 4, left). Regions of interest on non-ground surfaces are specified in cylindrical coordinates with a minimum and maximum height and azimuth angle (Fig. 4, right).

In the examples that follow, we use a ground region of interest with radius 2 to 10 meters and azimuth -60 to 60 degrees in the world coordinate frame. For non-ground regions, we use a region of interest with height 0 to 3 meters and azimuth -60 to 60 degrees in the world coordinate frame.

V. EVALUATING LADAR CONFIGURATIONS

In the absence of any domain-specific biases, a good

lidar configuration should sense the region of interest as densely and as uniformly as possible. The advantages of dense data are obvious, and it is also well-known that variations in data density can cause difficulties for algorithms that use such data [13]. We consider time-independent and time-dependent scenarios separately. The time-independent scenario is applicable to static scenes with a non-moving sensor, for example, if a robot periodically stops and uses the scanning lidar to take a high-resolution scan of the environment. In this case, a good configuration should consider point density and uniformity in the spatial domain, independent of the timing of the sampling. The time-dependent scenario, on the other hand, is more appropriate for dynamic scenes or moving sensors. In this case, a good configuration must optimize the density and uniformity of sampling in the temporal as well as the spatial domain. A configuration that works well for the time-independent scenario is not necessarily optimal for the time-dependent one, and vice versa.

VI. SPATIAL DATA DISTRIBUTION

The spatial distribution of samples on a surface model can be visualized using a plot of the data density (Fig. 5). We compute the data density by quantizing the surface model into cells and then computing a histogram of the frequency of laser points falling into each cell, normalizing by the cell surface area. The ground and object surface models are quantized into uniform square cells, while the non-ground surface model is quantized by height and azimuth, with the azimuth increment chosen to give

approximately square cells for the given radius of the cylinder. To reduce quantization effects, bilinear interpolation is used to distribute the contribution of each sample point into the four cells with centers closest to the sample point.

While data density is useful for visualization, it is difficult to compare such plots quantitatively. Therefore, we compute summary statistics for the region of interest – the average density (D_{avg}) and entropy (E). The average density is computed using equation (1) and is normalized by the total number of points sampled (N_{tot}) to eliminate the effect of different sampling period lengths.

$$D_{avg} = \frac{N_{int}}{A_{int} N_{tot}}, \quad (1)$$

where N_{int} is the number of points within the interest region and A_{int} is the area of the interest region.

Entropy is a common measure of data uniformity, with higher entropy being more uniformly distributed [14]. The entropy is computed using Equation (2).

$$E = \sum_{i,j} p_{i,j} \log(1 / p_{i,j}), \quad (2)$$

where $p_{i,j}$ is the fraction of points falling into cell $C_{i,j}$ and i,j iterate over the cells within the region of interest. We use the convention that when $p_{i,j} = 0$, then $0 \log(1 / 0) = 0$.

One limitation of this approach is that the computations are somewhat dependent on the choice of cell size. We found that a cell size of 0.5 m works well for the scale of outdoor

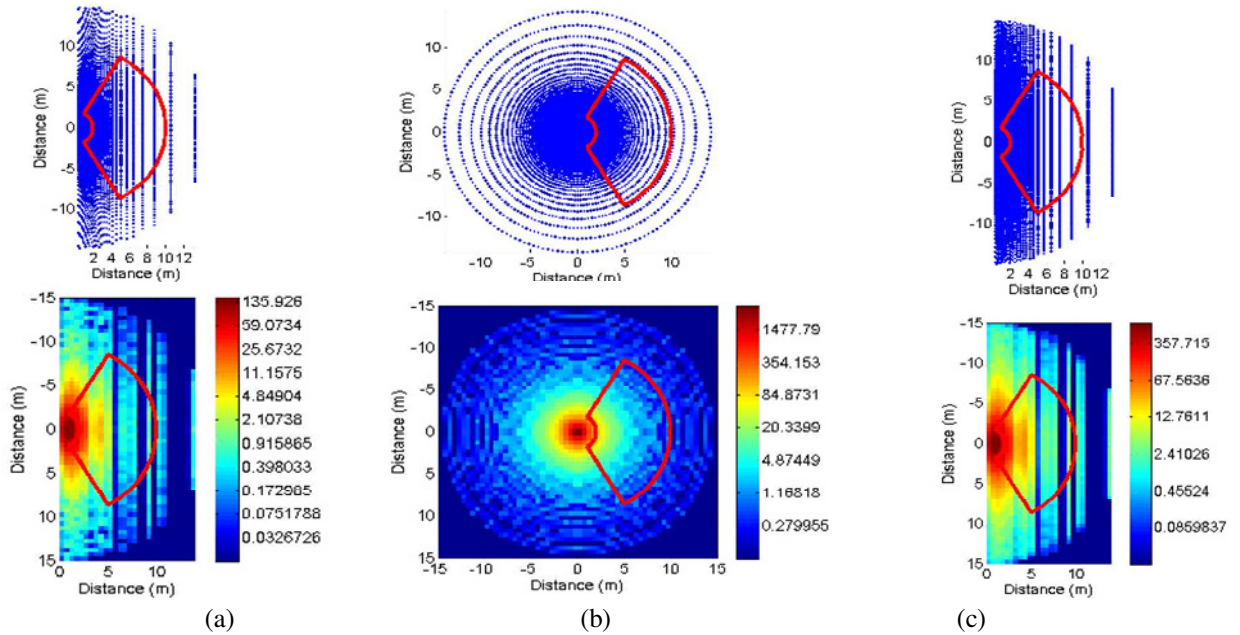


Fig. 5. Point measurement distributions (top row) and density plots (bottom row, log scale) for different scanning configurations. (a) nodding configuration using SICK LMS-291 parameters; (b) rotating configuration using LMS-291 parameters; (c) nodding configuration using Hokuyo UTM-30LX parameters.

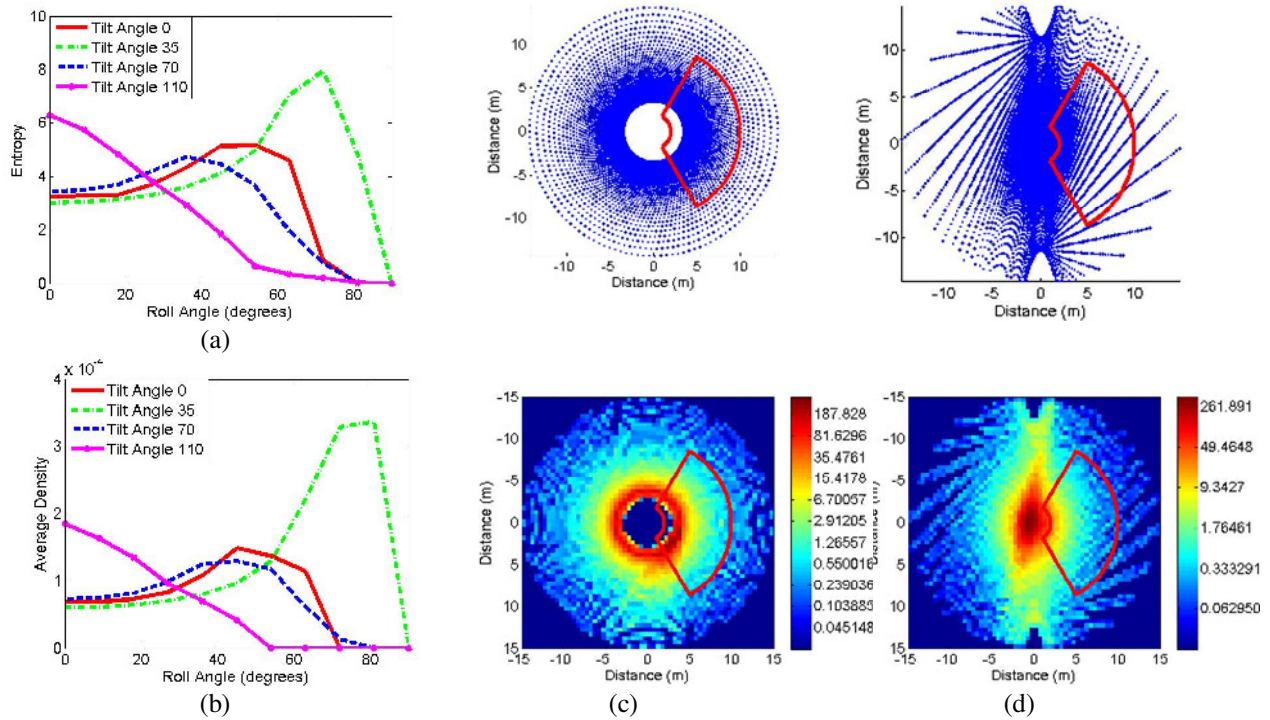


Fig. 6. (a) Plot of entropy (E) vs. roll angle (θ_R) for different values of tilt (0, 20, and 40 degrees) for points on the ground surface within the region of interest. (b) The corresponding plot of average data density (D_{avg}) vs. roll angle (θ_R). (c) The point measurement pattern and density histogram (log scale) for the maximum entropy configuration. (d) The point measurement pattern and density histogram (log scale) for a lower quality configuration.

mobile robots.

A. The effect of varying individual parameters

Using this framework, it is straightforward to simulate and visualize the data distribution patterns for common configurations of laser scanners. One common configuration is a nodding scanner in which the line of laser points is oriented horizontally and the scan head nods up and down (Fig. 5a) [4, 10]. Another configuration is a rotating scanner with the line of points oriented vertically and the scan head rotating about a vertical axis (Fig. 5b) [6].

It is also possible to compare different laser scanners for identical configurations. Fig. 5c shows the same configuration from Fig. 5a, but using the characteristics of the Hokuyo UTM-30LX line scanner. The Hokuyo samples points at three times the speed of the SICK and has an angular increment that is four times smaller, so the data density is much greater than for the SICK shown in Fig. 5a. Varying the pitch, roll, and tilt angles of the sensor can produce interesting variations in the scanning pattern. Fig. 6 shows the effect on entropy and average density values of varying the roll angle for various values of tilt (with the pitch angle set to 0).

B. Sensor Focus of Attention

One interesting aspect of the data density plot for a

nodding or rotating sensor is the degree to which the data density varies near the poles of the secondary rotation axis. It is intuitive that the data would be denser at the poles, but when this effect is combined with the effect of increasing density for closer surfaces that are viewed frontally, the degree of data density variation can be dramatic. For example, consider a rotating laser scanner with its secondary rotation axis vertical (Fig. 7). In this

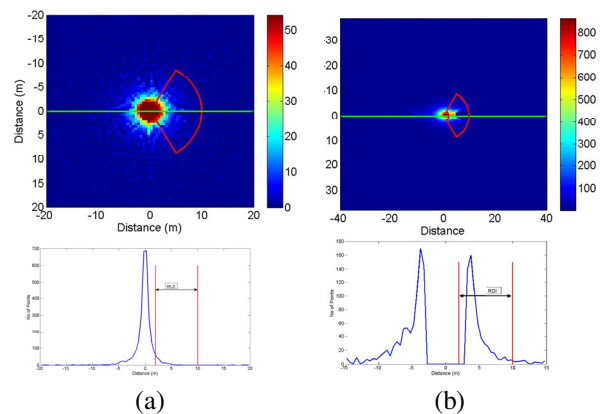


Fig. 7. Data can be extremely dense in the least useful regions for a bad configuration. (a) Data density plot for a ladar rotating about a vertical axis (top), and a cross-section of the plot at the point indicated by the line (bottom). (b) Data density for a configuration with the rotation axis tilted to achieve high density in front of the vehicle (top), and the corresponding cross-section (bottom).

configuration, the maximum data density on the ground is over 100 times the density of data 6 meters away from the sensor. This dense data region occurs directly under the sensor, which is probably the least useful location to sense because this region would typically be on the vehicle itself. Similarly, for a forward-looking nodding sensor, the dense data regions at the poles are located to the side of the vehicle, which is not helpful for most tasks.

One alternative is to point the pole of the sensor toward the direction of interest. This idea has been used by other researchers in the past, where the secondary axis of a rotating sensor is pointed straight forward in the direction of travel [2, 3, 7]. A slight modification of this strategy is to point the pole slightly downward so that the dense data region is a fixed distance ahead of the vehicle on the ground.

The dense data at the poles is analogous to the dense sensing in the fovea of the human eye. Just as a person uses focus of attention to gain high resolution data in regions of importance, a laser scanner could use its polar “foveal” region more effectively by dynamically pointing it in the direction of interest. For example, the foveal region could be constantly focused on a region that is N seconds ahead of the vehicle, focusing closer when the vehicle slows and further when it speeds up.

Pointing the axis of rotation at the region of interest does not necessarily give the highest average density or best uniformity. Fig. 6a shows that the entropy for tilt angle 110° , which aims the axis of rotation at the center of the region of interest, gives an entropy of about 6, but an alternate configuration, with a tilt angle of 35° , gives an even higher entropy value of over 8. The average density plots have a similar pattern, but the maximum is at a slightly different location. These results suggest that the intuitive notion of pointing the rotation axis at the area of interest may be too simplistic an approach, and that more sophisticated pointing strategies could yield denser and more uniform sensing patterns.

VII. SPATIO-TEMPORAL DATA DISTRIBUTION

When the sensor is on a moving platform, or if the environment contains moving objects, then the spatial data distribution measure described above does not capture the temporal aspect of the data distribution, which can be misleading for sensor configuration decision-making. For example, to obtain dense data measurements, one strategy is to nod/rotate the sensor head very slowly (i.e., choose a small secondary angular increment). However, the time between subsequent measurements in one physical location could be very large in this case. If the sensor or objects in the environment are moving, this slow nodding/rotation could lead to significant parts of the environment never getting imaged at all. Therefore, it is important to consider

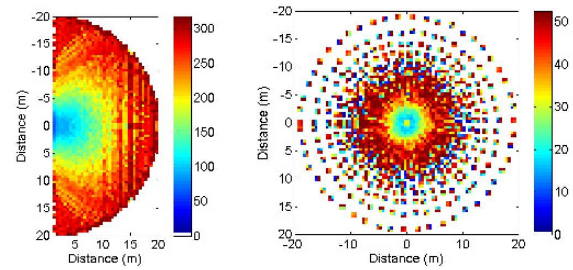


Fig. 8. The spatio-temporal entropy plots for a nodding lidar (left) and a rotating lidar (right).

the uniformity of measurement distribution across time as well as space.

Our method for evaluating spatial uniformity can be extended to incorporate temporal uniformity as well. In this case, the two dimensional surfaces become quantized three dimensional volumes, where time is the third dimension. Measurements are inserted into the volume using trilinear interpolation, and average density and entropy are computed over the volume of cuboid cells. The relative size of the cells in the temporal dimension with respect to the spatial size of the cells can be used to adjust the balance between the importance of spatial uniformity and temporal uniformity, and is a task-specific parameter.

One way to visualize the temporal uniformity of a sensor configuration is to compute the entropy over time at each spatial location. At each spatial cell ($C_{i,j}$), all the cells in the temporal dimension are used to compute a single entropy value ($E_{i,j}$), and the resulting 2D plot of entropy shows the temporal uniformity across the region of interest. Fig. 8 shows this type of entropy plot for a nodding and a rotating sensor. Notice that the entropy for the nodding configuration is much higher than for the rotating configuration, since the nodding configuration covers a much narrower field of view at a faster rate.

A. Effects of Varying Sensor Angular Increment

The primary angular increment is typically fixed by the sensor choice, but the secondary angular increment is usually a controllable parameter in nodding/rotating scanners, since it is directly related to the secondary rotational velocity. The choice of this parameter can have significant influence on the spatial or spatio-temporal uniformity of the data. For a rotating sensor, choosing a value that is a factor of 360° will result in a data distribution where the physical location of measurements repeat with each rotation. While this may be adequate for moving sensors, when the sensor is not moving, there can be significant gaps between the measurements, which can make it hard to detect or track smaller objects. More concretely, a 10° angular increment results in a 1.75 m gap between measurements at a distance of 10 m, which could

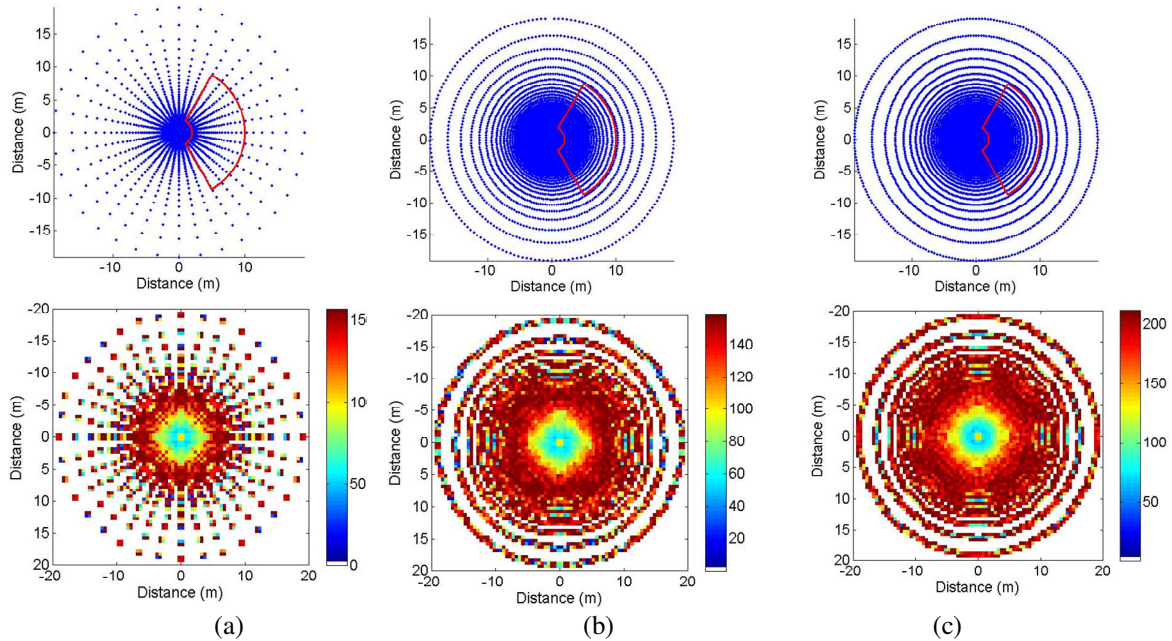


Fig. 9. Data distribution patterns (top row) and spatio-temporal entropy plots (bottom row) for different choices of angular increment. (a) An even factor of 360 degrees ($M = 10$ degree) leaves large gaps. (b) Choosing M' according to equation (3) ($M=10, N=5$) gives better spatial uniformity, but poor spatio-temporal uniformity; (c) Choosing M' according to equation (4) ($M=10, f=5/7$) gives good spatial and temporal uniformity.

easily permit missed detections of a person (Fig. 9a). If, instead, the angular increment is not a factor of 360° , then the measurement locations will not repeat each time.

One simple way to adjust the angular increment is to ensure that the measurements repeat only every N rotations. If the desired angular increment is M , then choosing the angular increment so that one more (or one less) than the expected number of measurements occurs in N rotations will result in a measurement angle that changes by $1/N^{\text{th}}$ of the angular increment each rotation. More precisely the new angular increment M' should be:

$$M' = \frac{2\pi N}{(2\pi N / M) \pm 1} \quad (3)$$

One disadvantage of this approach is that the gap between the initial measurements is filled incrementally, so that the spatio-temporal distribution of the data is not very good (Fig. 9b). Ideally, the points would be distributed uniformly in the temporal domain as well. With a constant velocity rotation, only a limited amount of uniformity is possible. If the angular increment is chosen so that subsequent measurements fall at specific fractions of the initial angular increment, better spatio-temporal uniformity can be achieved. Fractional values of 0.6 ($3/5$), 0.7143 ($5/7$), and 0.7778 ($7/9$) give desirable patterns. Equation (4) can be used for this:

$$M' = \frac{2\pi + fM}{2\pi / M + 1}, \quad (4)$$

where f is the fractional value. For example, if M is 10 degrees and f is $5/7$, then M' is 9.923 degrees, and the

resulting pattern is shown in Fig. 9c. Our spatio-temporal uniformity measure shows the benefit of choosing the angular increment using this strategy, since the entropy values are much higher in Fig. 9c than in Fig. 9a and b. An alternative to choosing the angular increment using these formulas is to search for the best parameter value through optimization, which is the subject of ongoing work.

B. Modeling Moving Sensors

If the lidar is mounted on a mobile robot, the sensor may not be stationary. Our approach can also evaluate sensor configurations on moving platforms. In such cases, we modify the sensor simulator to model sensor motion. We have implemented linear motion paths, but the extension to more complex motion trajectories is straightforward. A linear motion is accomplished by translating the platform coordinate frame in a direction P_l with a velocity P_v with respect to the world coordinate frame.

For moving sensors, we limit the analysis to ground surface and object models. The non-ground cylindrical surface does not make sense in this situation, because real objects would not move with the sensor platform. Instead, we use strategically placed object models to study the effect of motion on data density and uniformity. Fig. 10 shows an example of a data density plot for a moving sensor. In this example, the region of interest is 18 m on either side of the sensor and covers a fully imaged region along the traverse.

VIII. SUMMARY AND FUTURE DIRECTIONS

We have presented a method for objectively evaluating lidar sensor configurations. The method considers data

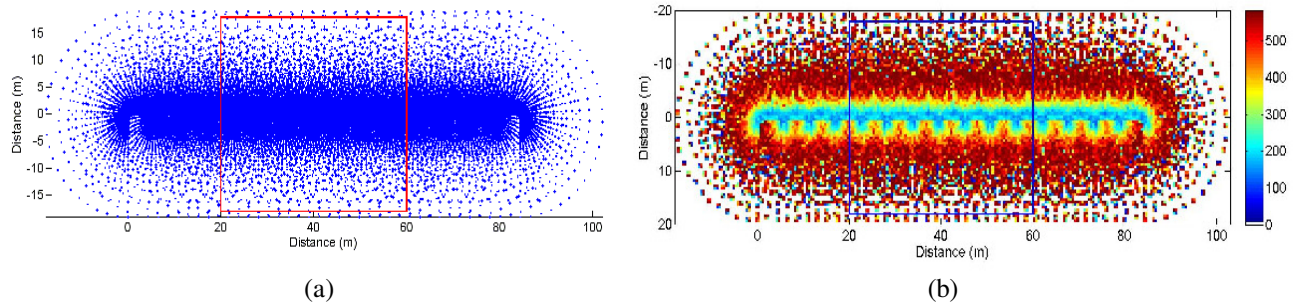


Fig. 10. An example of evaluating a moving sensor. (a) Ground points for an 85 meter traverse. (b) Spatio-temporal entropy plot of the ground.

density and uniformity. We showed that a simple lidar simulator can be used to generate the data needed to evaluate a lidar system, and that the space of possible lidar configurations for a line scanner that mechanically nods/rotates includes configurations that are not typically considered when designing and integrating a lidar sensor system. Tilting and rolling the sensor can greatly improve the data density and uniformity within the region of interest, as can strategically (and potentially dynamically) aiming the polar region of a rotating sensor. Our method is applicable to static environments, but can also be extended to incorporate the temporal aspects that are critical for scenarios in which the sensor or objects in the environment are moving. We found that the choice of the sensor rotation rate is important to achieving high spatio-temporal uniformity, and we offered strategies for choosing the rate to provide good data distribution patterns. Our next step is to add an optimization algorithm to search for the optimal set of configuration parameters within this framework. The challenge here is that the space of possible lidar configurations is relatively high-dimensional (at least 11 parameters could be considered). The space is continuous, and is likely to have many local minima, which limits the effectiveness of gradient descent-based optimization. We are considering using a global optimization method, such as simulated annealing, to address these challenges.

We emphasize that the approach that we have taken is only one possible implementation of this general idea. Each of the components of the framework (the simulator, the surface models, the data quality measures) could be replaced by more sophisticated or specialized alternatives. For example, the lidar simulator could be extended to explicitly model measurement uncertainty or data artifacts produced by a particular lidar. Different terrain shapes could be tested by a more advanced terrain modeler. It would be interesting to experiment with the effects of changes in terrain slope, such as steep downward slopes that occur when a robot crests a hill. Other measures of data quality are possible and might prove to be more reliable. One potential disadvantage of our proposed data quality measures is that they measure general qualities of the data rather than directly relating to the performance of a

particular algorithm. If our method were integrated into a complete robotic system, it would be possible to directly learn the relationship between sensor configuration and algorithm performance. We hope to study these extensions in future research.

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