Surface Normal Estimation from Noisy, Single-Photon Lidar Point Clouds

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Introduction

Lidar is an imaging method used to determine scene properties by targeting a surface with a laser and measuring the time-of-flight of returned photons. Today, lidar data from real-world applications such as autonomous navigation and augmented reality contains undesirable noise from the background that impacts estimates of surface normals, which are important scene parameters indicating the orientation of the imaged surface. This poster studies the impact of noise on normal estimation techniques with both simple and complex scene geometries using known mathematical equations and the classical Delaunay Triangulation[1] method. The Euclidean distance between the noiseless and noisy normal estimates is used to quantify the impact of noise. In addition, the effect of the number of neighboring pixels involved in Delaunay Triangulation and the broadening effect in single-photon lidars are also discussed. Single-photon lidars have only one detected photon for each measurement and the broadening effect refers to the broadening of the scene impulse response due to its inclination relative to the laser line-of-sight.

Broadening Effect

The full widths at half max of received lidar signals received at a SPAD (single photon avalanche photodiode) vary with the angle of inclination between the surface normals and the laser line-of-sight. By accurately modeling this broadening effect[2], we can jointly estimate the depth and angle of inclination of each point in a lidar point cloud. This additional information can lead to better normal estimates in noisy conditions where traditional methods that rely on accurate depth estimates do not perform well.

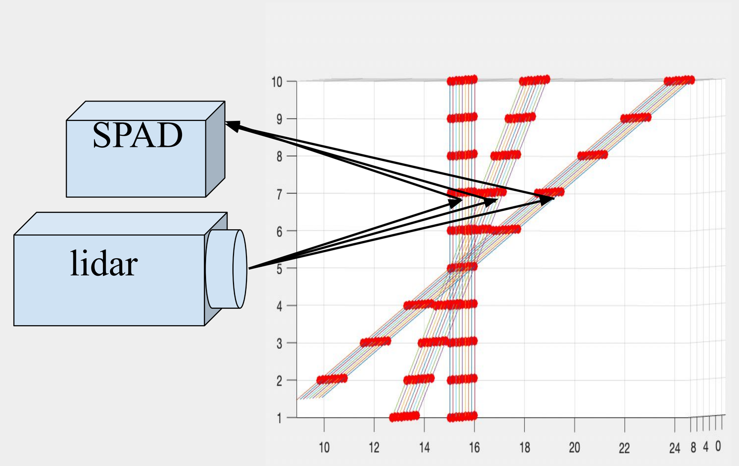
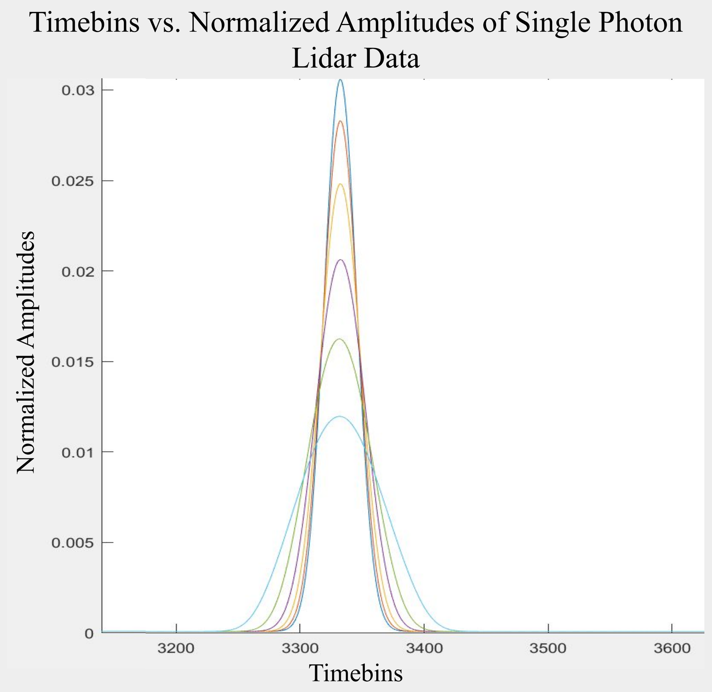


Figure 1.1: Broadening of received lidar signals due to various tilt angles of the imaged surface.



Simple Geometric Scenes

Concave Caps

First, simple geometric scenes are created using known mathematical equations to verify the performance of classical normal estimation techniques. For example, using derivatives, given the equation of a sphere, $r^2 = x^2 + y^2 + z^2$, the coordinates of the surface normal vectors are $< 2x, 2y, 2z >$, which are shown in Fig. 2.1. Then, random white Gaussian noise is added to the concave cap, producing Fig. 2.2, where the red arrows represent the ground truth normals and the blue arrows showing the new surface normals due to the added noise. These plots were then compared with the results of Delaunay Triangulations to verify that normals estimated through Delaunay Triangulations are accurate and vice versa.

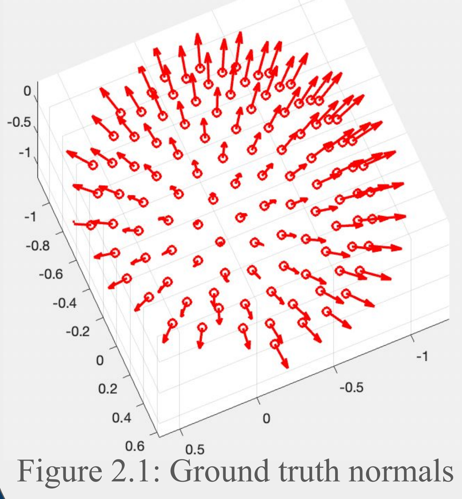


Figure 2.1: Ground truth normals for a Sphere with Radius = 1

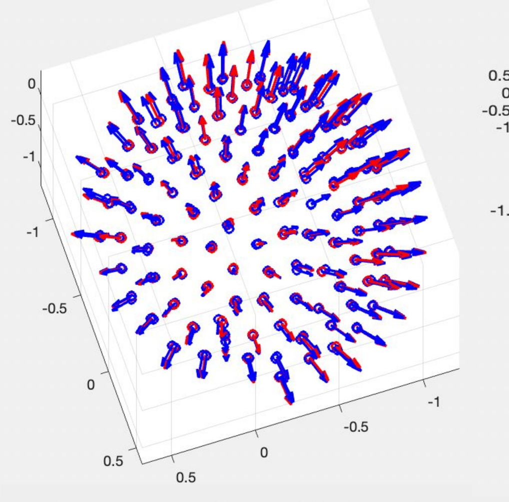


Figure 2.2: Effect of light noise on surface normals.

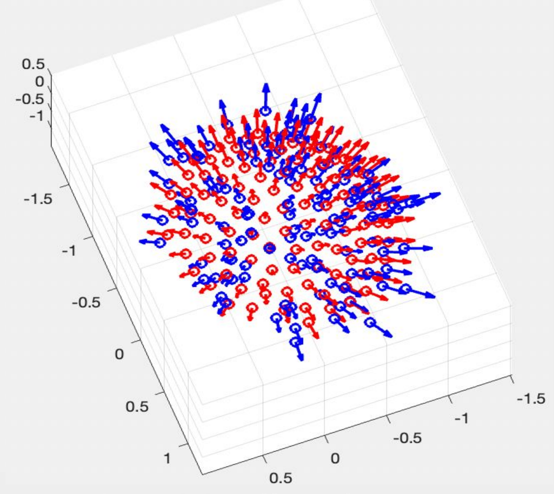


Figure 2.3: Effect of extreme noise on surface normals.

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Complex Geometric Scenes

Stanford Data Sets

Using two different datasets from the Stanford 3D Scanning Repository[3], surface normals are estimated using Delaunay Triangulation on MATLAB, which differs from how surface normals were estimated using the derivatives of mathematical equations in the simple geometric scenes. Next, the number of neighboring pixels used in the Delaunay Triangulation is varied to study the relationship between the standard deviation of the random white Gaussian noise added and the average Euclidean distance between the noisy and noiseless points, which is referred to as the error.

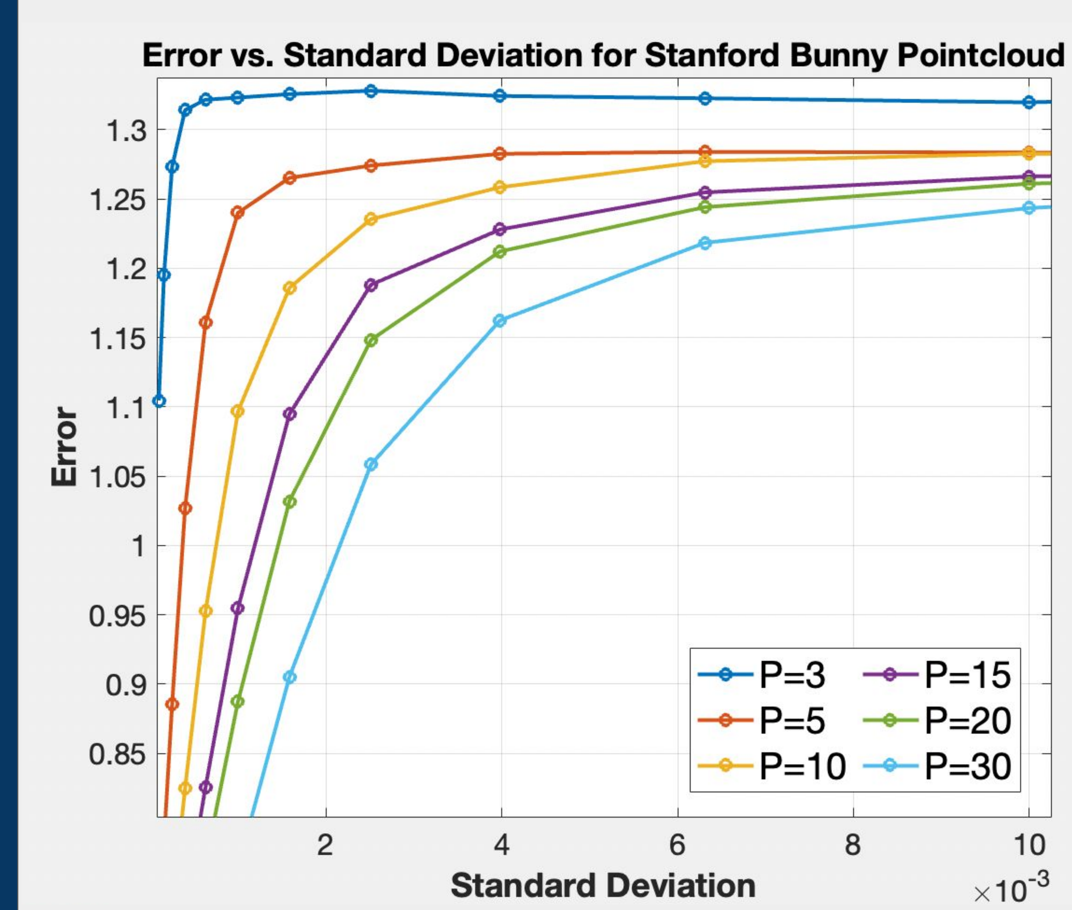

Figure 3.1: Graph showing the error vs. standard deviation for various numbers of neighboring pixels, P, using the Stanford Bunny Point Cloud.

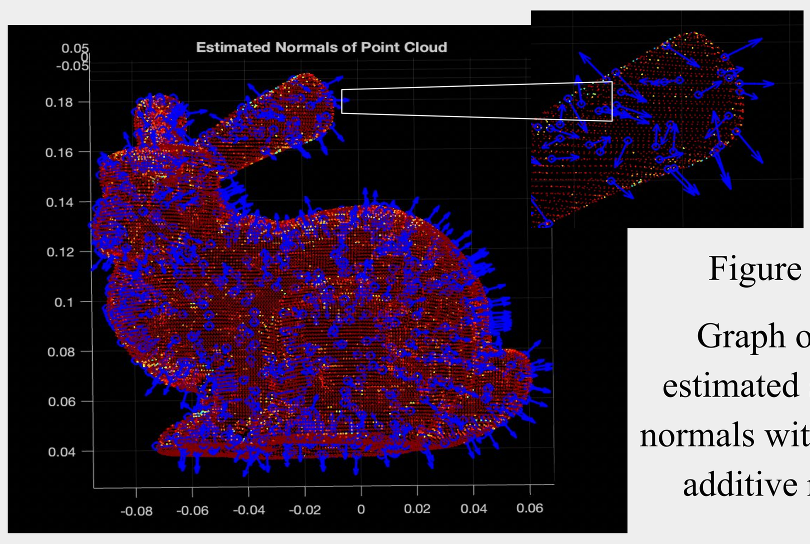

Figure 3.2: Graph of the estimated surface normals without any additive noise.

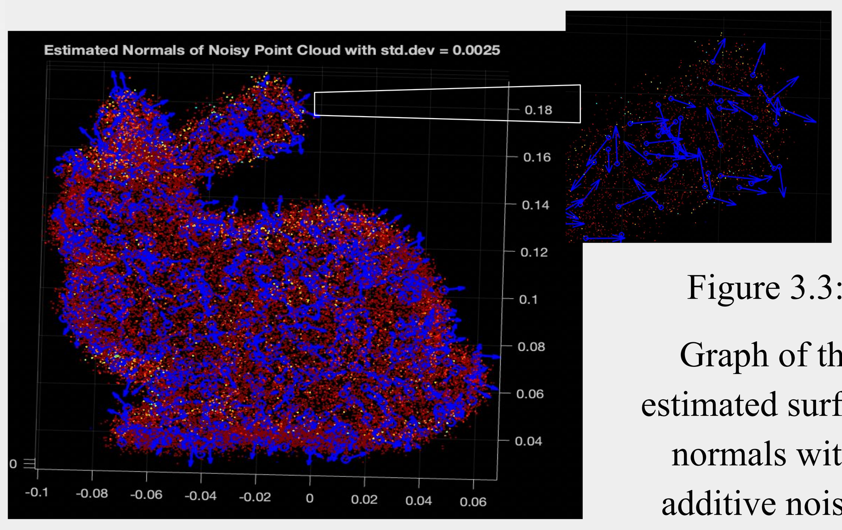

Figure 3.3: Graph of the estimated surface normals with additive noise.

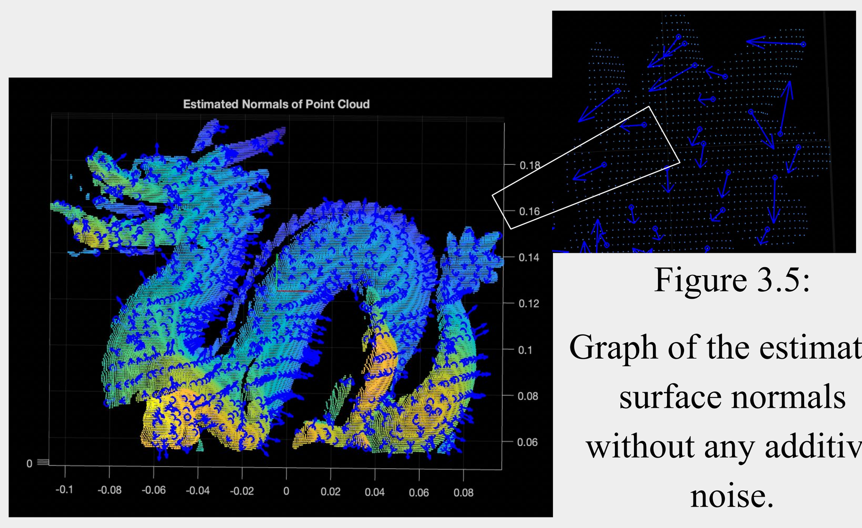

Figure 3.5: Graph of the estimated surface normals without any additive noise.

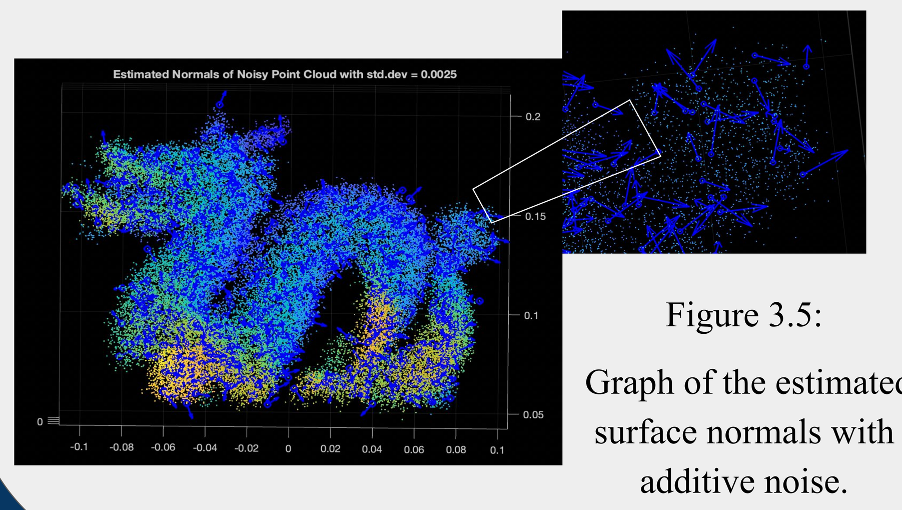

Figure 3.5: Graph of the estimated surface normals with additive noise.

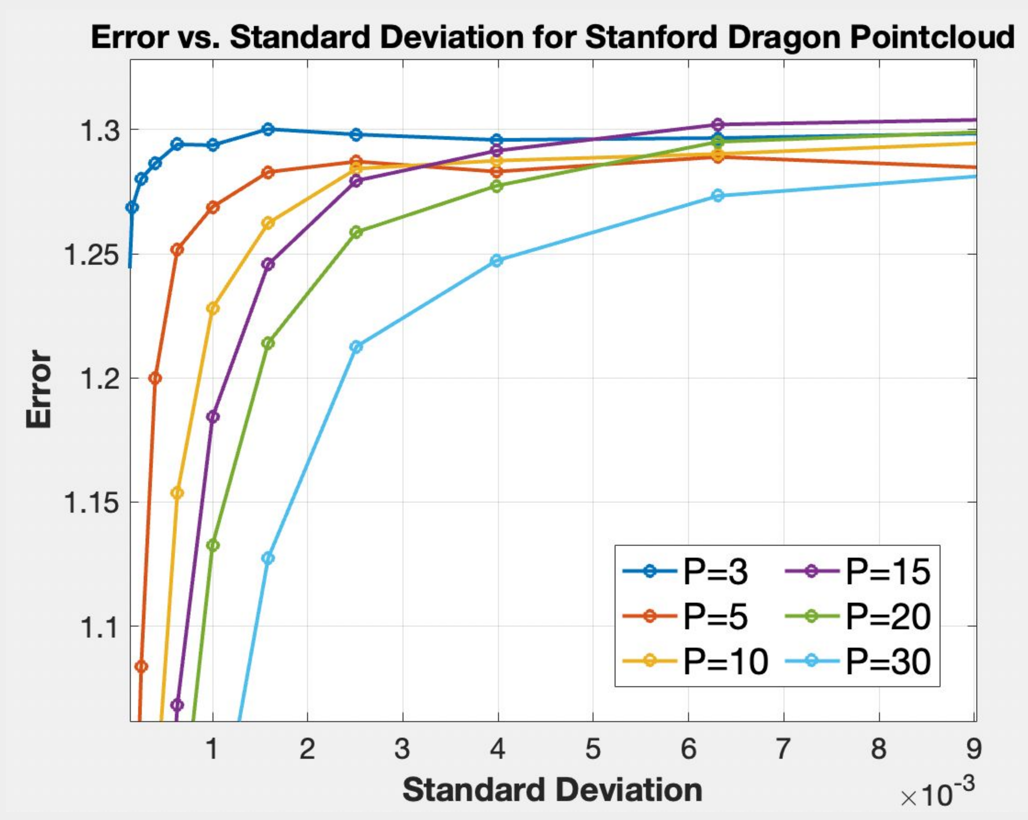

Figure 3.4: Graph showing the error vs. standard deviation for multiple P values using the Stanford Dragon Point Cloud.

Discussion and Conclusion

I. Analysis of Complex Geometric Scenes Graphs

Fig. 3.1 and Fig. 3.4 shows that when the standard deviation of additive white Gaussian noise is low, as the number of pixels used to determine the surface normal increases, the average Euclidean distance between the noisy estimates and the ground truth reduces. However, as the standard deviation increases, this relationship is less obvious. Thus, under noisy conditions, traditional normal estimation techniques do not perform very well.

II. An Additional Degree of Freedom

Delaunay Triangulation relies only on the depth estimate of points in a dataset to determine the best fitting plane at each local neighborhood. However, depth estimates can be extremely inaccurate in scenarios where the measured signal-to-noise ratio is very low. Hence, in such cases, by exploiting the broadening effect to calculate an additional measurement at each point, namely the tilt angle, better estimators can be developed which mitigate the effect of noise and is a subject for future research.

References

[1] Musin, O. R. Properties of the Delaunay Triangulation. In *Proceedings of the thirteenth annual symposium on Computational geometry - SCG '97*; ACM Press: New York, New York, USA, 1997.

[2] Hao, Q.; Cao, J.; Hu, Y.; Yang, Y.; Li, K.; Li, T. Differential Optical-Path Approach to Improve Signal-to-Noise Ratio of Pulsed-Laser Range Finding. *Opt. Express* 2014, *22* (1), 563–575. https://doi.org/10.1364/OE.22.000563.

[3] *The Stanford 3D scanning repository*. Stanford.edu. http://graphics.stanford.edu/data/3Dscanrep/ (accessed 2022-08-09).