Homework 3

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AuE 8930: Machine Perception and Intelligence

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* Refer to Syllabus for homework grading, submission and plagiarism policies;
* Submission files includes (Due March. 25, 2020 11:59 pm):

- This document file (with answers), and with your program results/visualization;
- A .zip file of source code (and data if any) with names indicating question number;

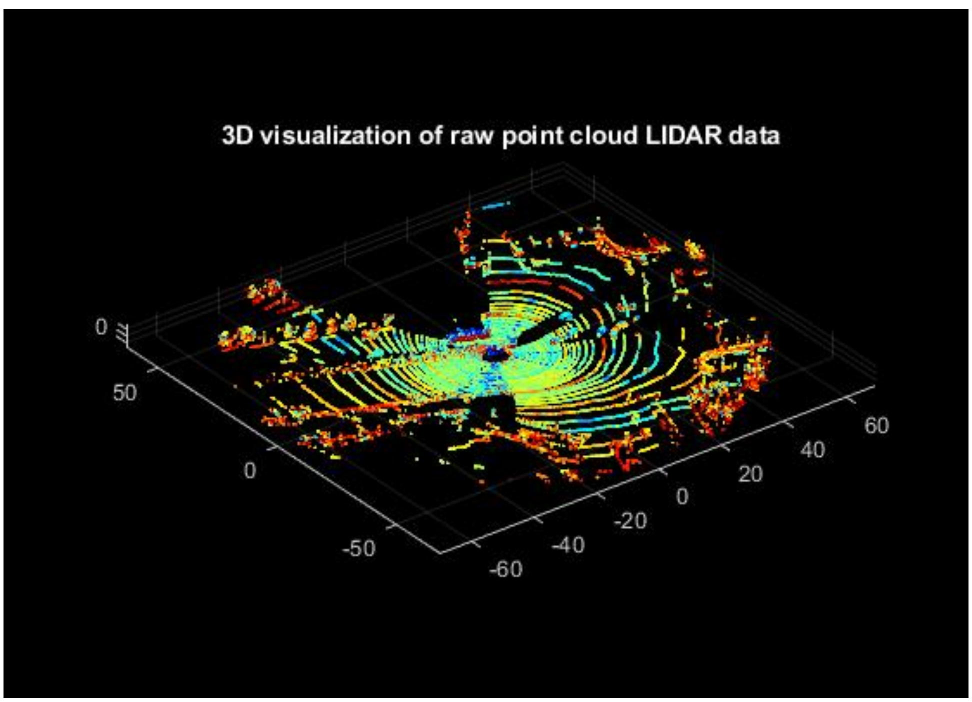
<u>Note:</u> You can use any 3rd party libraries and built-in functions

Download the Apollo "Lidar Point Cloud Obstacle Detection & Classification" dataset and description (LiDAR_datasets.zip and LiDAR_datasets_description.pdf) from Canvas/File Homework 3 folder: This Lidar dataset is collected from a 3D Velodyne HDL-64E Lidar. You will find the .bin (point cloud) files for each scanning frames. Please pay attention that in the description pdf, it says:

- The point cloud data are stored in the format of binary files.
- The data are arranged in the order of X1, Y1, Z1, I1, X2, Y2, Z2, I2… (Xi, Yi, Zi refer to the spatial 3D coordinates of each point.
- Ii represents the reflectance value of this point and the effective value of the reflectance value is from 0 to 255)
- The data in each dimension are stored as the four-byte float type.

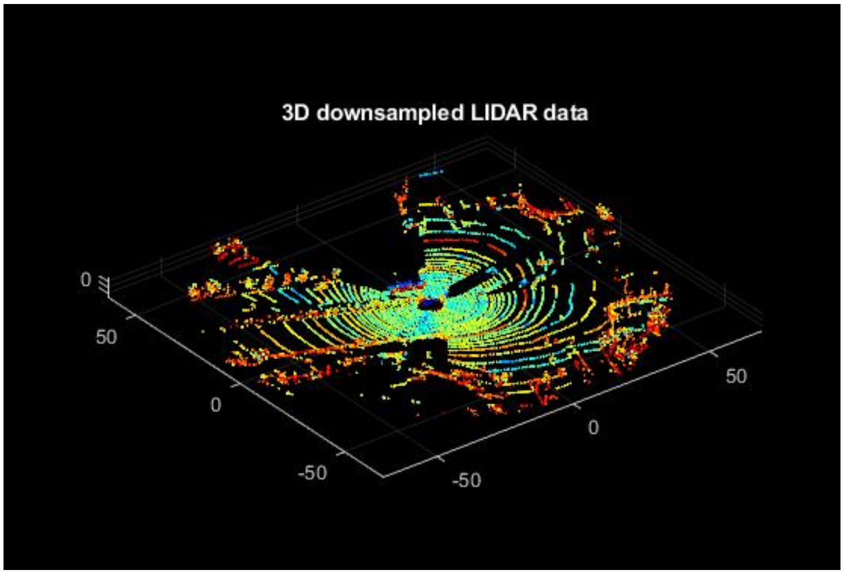
Question 1) [10 pts]

Select a frame (or a few frames) of LiDAR data file, parse the file and visualize the 3D point cloud of this frame, colored by its reflectivity value.



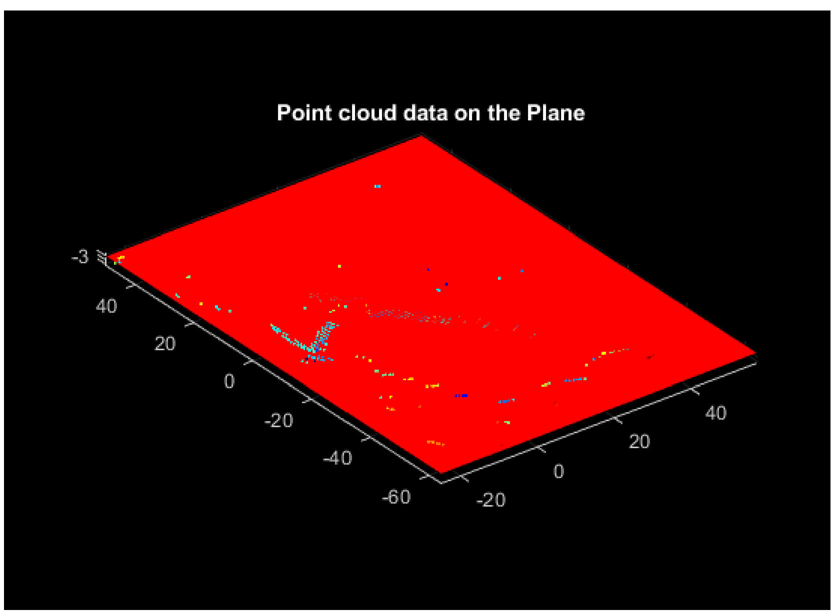
Question 2) [10 pts]

Choose a 3-D resolution granularity, perform voxel filter (or box grid filter) to down-sample all the 3D point cloud points to the 3D voxel space points, and visualize the result points;



Question 3) [20 pts]

- Apply RANSAC algorithm (or any others you prefer) to the 3D voxel space points to find a ground plane model. Print out your plane model parameter values result, visualize the plane with the points in the 3D (10 pts);
- Analyze the computational time complexity of this algorithm (5 pts).
- Remove all the ground planes points in the 3D voxel space points, visualize all the off-ground points in the 3D (5 pts);



```
tic %%% Computational time complexity verification
maxDistance = 0.02;
referenceVector = [0,0,1];
maxAngularDistance = 0.1;
[model,inlierIndices,outlierIndices] = pcfitplane(ptCloudA,maxDistance,referenceVector,maxAngularDistance);
plane1 = select(ptCloudA,inlierIndices); %%% 3D point cloud data is selected with respect to planes of choice
remainPtCloud = select(ptCloudA,outlierIndices);
roi = [-inf,inf;0.4,inf;-inf,inf];
sampleIndices = findPointsInROI(remainPtCloud,roi);
[model2,inlierIndices,outlierIndices] = pcfitplane(remainPtCloud,...
            maxDistance,'SampleIndices',sampleIndices);
plane2 = select(remainPtCloud,inlierIndices); %%% 3D point cloud data is selected with respect to planes of choice
remainPtCloud = select(remainPtCloud,outlierIndices);
figure(3)
pcshow(plane1)
hold on;
pcshow(plane2)
hold on;
plot(model1)
title('Point cloud data on the Plane')
toc %%% The elapsed time gives the time complexity of the RANSAC algorithm to compute
```

Command Window

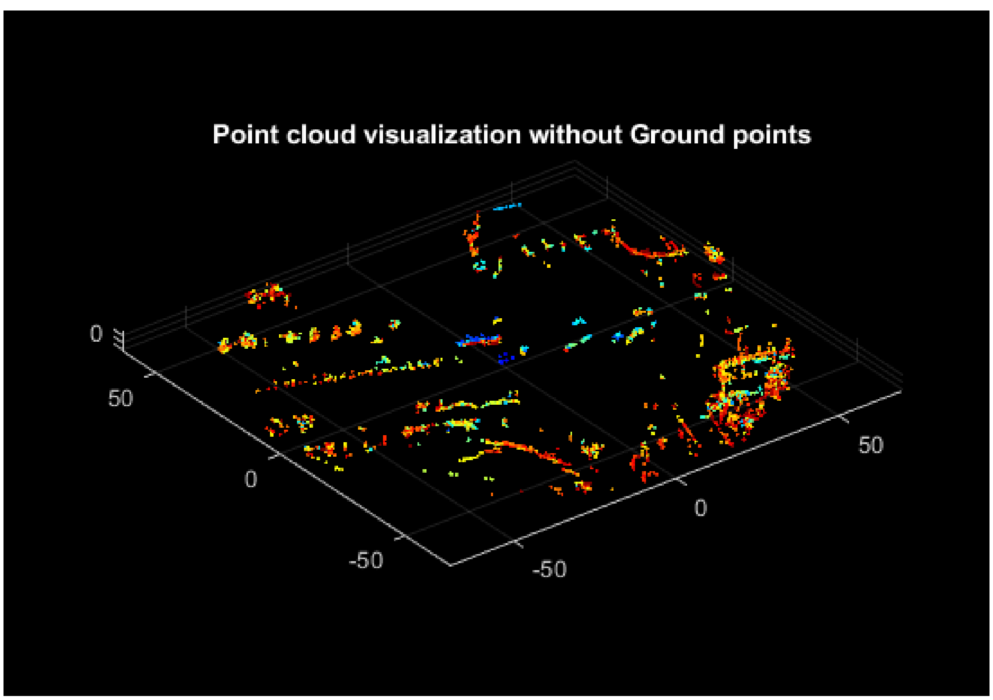
New to MATLAB? See resources for Getting Started.

```
>> Assignment3_Perception
Elapsed time is 1.009881 seconds.
```

The computational time complexity of the RANSAC's variant- MSAC (M-estimator SAmple and Consensus algorithm) would be calculated by using the tic and toc functions in MATLAB as mentioned above. In general, the implementation of this new method (MSAC algorithm) yields a modest to hefty benefit to all robust estimations with no additional computational burden. Once this is understood there is no reason to use RANSAC in preference to this method. Also, the computational time complexity can be calculated for the RANSAC algorithm as:

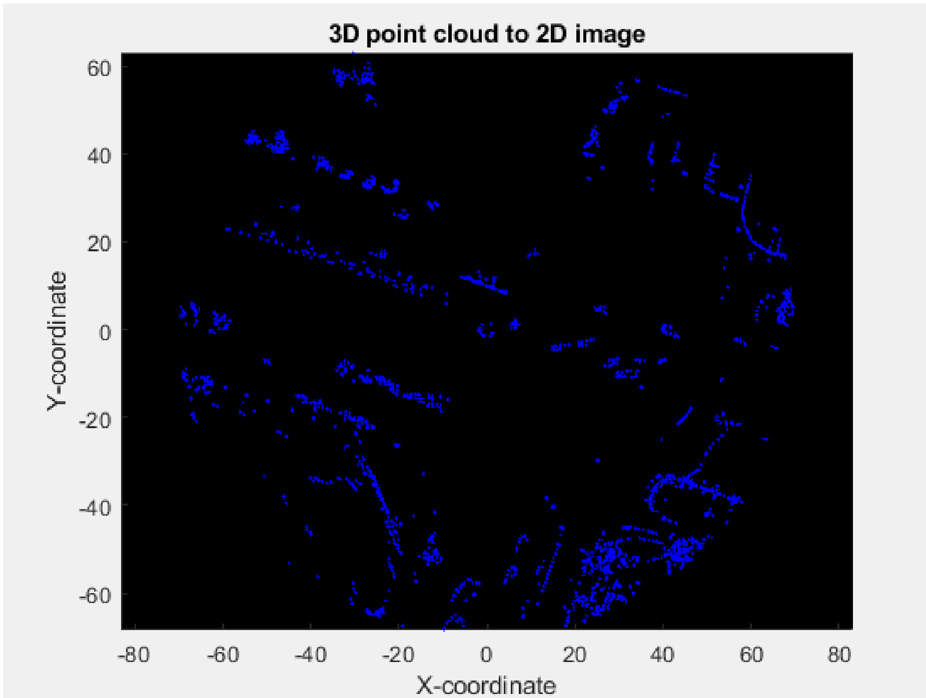
$$\text{Complexity} = O\left(T_{iter}\left(C_{estimate}(k) + NC_{fitting}\right)\right)$$

Reference: http://www.cs.tau.ac.il/~turkel/imagepapers/RANSAC4Dummies.pdf



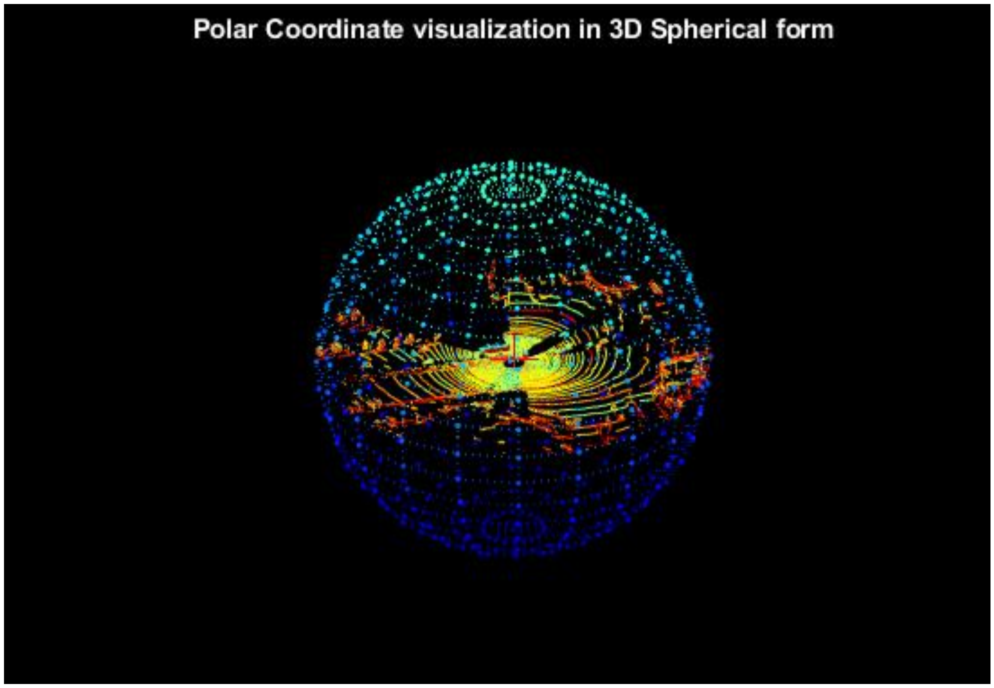
Question 4) [10 pts]

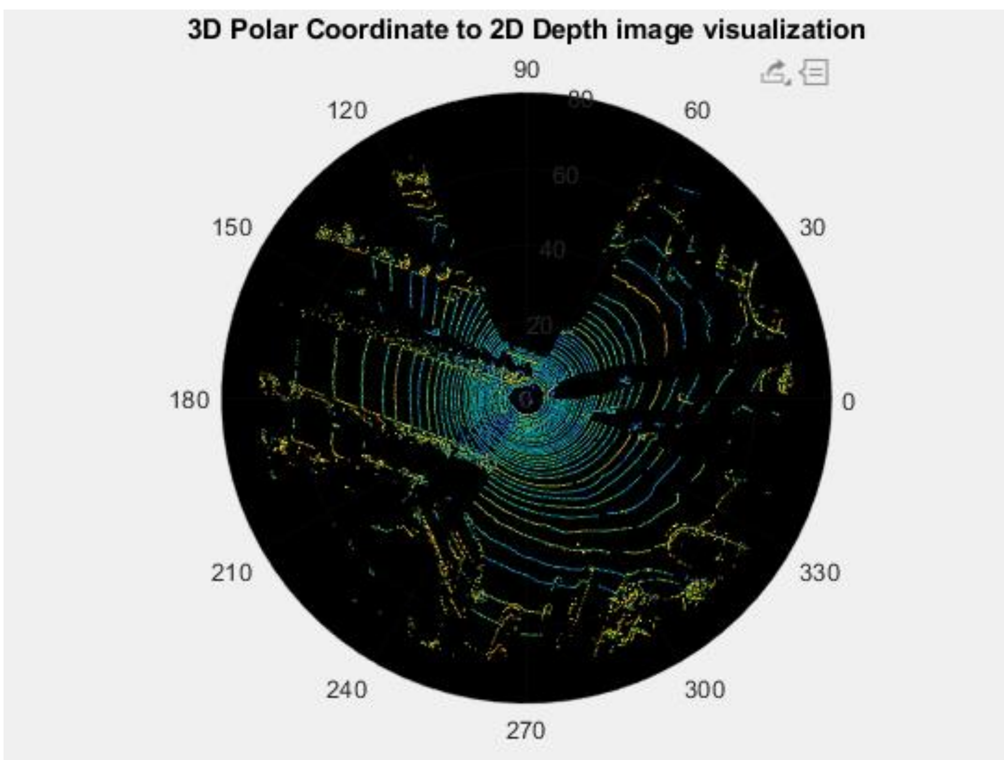
Perform a x-y projection to the off-ground points, and get a 2D matrix (you decide what is the element value), and visualize the 2D matrix as an image.



Question 5) [10 pts]

- Based on the raw point cloud data (Questions 1), which is in Cartesian Coordinate, represent and visualize all the point cloud in Polar Coordinate (with horizontal and vertical angels and distance to the original) (5 pts).
- Finally, generate the projected 2D depth image w.r.t horizontal and vertical angels, with intensity value using the distance. Visualize the 2D depth image (5 pts).





Question 5) [40 pts]
Write 2~3 pages of survey on a 3D data measurement related to vehicles.
The grading of this question is based on the contents which the survey covers:
- The importance of this physical quantity measurement (5);

- The challenges of measuring this physical quantity (5);
- Existing solutions of measuring this physical quantity (15);
- Existing problems of measuring this physical quantity (5);

There will be other grading factors (such as novelty, organization, et al) (10);

* You are encouraged to include any drawing/table in the report;
* Attention: use "…" [1] to cite any sentence you literally copied and use … [1] to cite a content you referred to, with reference list in the end;

Abstract:

Recently many innovative vehicle safety systems and various advanced driver assistance systems (ADAS) have been presented to the public and been introduced in the market. One way to satisfy the demand for reliable active and passive safety applications research activities are concentrating on the fusion of multiple sensors in the car. The aim is to create intelligent vehicles by equipping them with the ability to perceive the vehicles environment and thus to be able to warn and protect the passenger as well as other vulnerable users on the road (pedestrians, bikers, cyclists). Most driver assistant and safety systems address this issue by using different sensors in multiple configurations. The challenge for these systems is nowadays the accurate and reliable environment perception by evaluating the sensor data. This can – among others – be done by methods of data fusion of the car's sensor devices. The main way here to satisfy the demand for ADAS through vehicle perception is 3D LIDARs.

Importance of measuring 3D LIDAR data:

In the automobile perspective, it is very important to measure the 3D LIDAR data because, they are used for many purposes like navigation, autonomous cruise control, obstacle detection, and collision avoidance. They serve the purpose of maintaining the stability of the vehicle reducing the accident and thereby ensuring the safety of the passengers. With various perception sensors involved in the vehicle, the 3D LIDAR will be advantageous over the other sensors because of their higher accuracy in the point cloud data [1]. The fast acquisition and procession of the data will help in predicting the other vehicles and creating bounding boxes with relatively less time. 3D LIDAR usually has less human dependence making the processes automatic, unlike photogrammetry and GNSS. It is also important to measure the 3D LIDAR data because they provide support with the canopy penetration. This is because the 3D LIDAR pulses can reach beneath the canopy thus generating measurements of points there. Moreover, the 3D LIDARs observe the amplitude of backscatter energy thus recording a reflectance value for each data point. The 3D LIDAR can also be used for perception tasks because of the higher data density where multiple returns are there to collect the data in 3D.

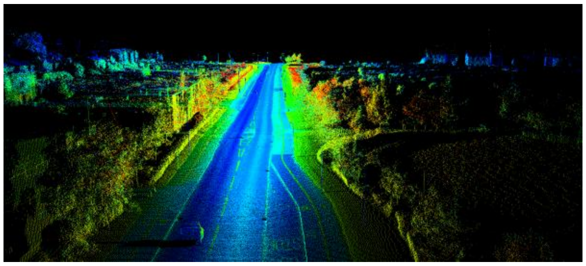


Figure 1 3D LIDAR point cloud (https://www.geospatialworld.net/news/lizardtech-awarded-us-patent-lidar-point-cloud-compression-2/)

Challenges of measuring the 3D LIDAR data:

There are many challenges involved in measuring the 3D LIDAR data like the ineffectiveness during the heavy rain or low hanging clouds [2]. The 3D LIDAR pulses may be affected by heavy rains or low hanging clouds because of the effects of refraction. The 3D LIDAR technology does not work well in areas or situations where there are high sun angles or huge reflections since the laser pulses depend on the principle of reflection. Adding to this, when the 3D LIDAR is used on the water surfaces or where the surface is not uniform, it may not return accurate data since high water depth will affect the reflection of the pulses. Moreover, 3D LIDAR technology has difficulty in collecting very huge datasets that require a high level of analysis and interpretation. This requires very high computing power and a lot of time for performance. Although 3D LIDAR is used in many ways, there is a limitation in usage because of the operating altitude because the pulses will not be effective at high altitudes [3]. The data will be too high since a lot of information in a 3D point cloud will be collected and parsing is needed for further processing which takes a considerable amount of time. Perhaps, a single data point may not be valid because it will be fraught with uncertainty and may or may not represent the correct and reliable information.

Existing solutions to measure the 3D LIDAR data:

There are many solutions present to measure the 3D LIDAR data where the measurement estimation comes into a play.

Pulsed approach:

Pulsed time of flight techniques are based on the simplest modulation principle using the illumination beam where the distance is determined by multiplying the speed of light in a medium by the time the light takes to travel the distance to the target. Here, since the speed of light is constant and the same medium is present, the distance to the object is directly proportional to the travelled time. The measured time means twice the distance to the object, as light travels to the target twice and half the value will be taken for calculation of the time of flight and the distance [4]. The pulsed approach is, despite its multiple limitations, the most frequently used one because of its simplicity and capability to perform well outdoors.

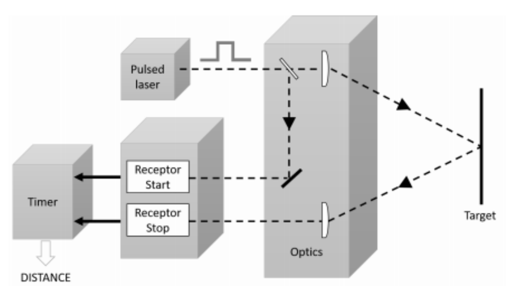


Figure 2 Pulsed Approach chart
(https://www.researchgate.net/publication/336173773_An_Overview_of_Lidar_Imaging_Systems_for_Autonomous_Vehicles/figures?lo=1)

Continuous Wave Amplitude Modulated (AMCW) approach:

The laser pulses by the intensity modulation of a continuous light wave is known as the CW modulation and the phase-shift induced in an intensity modulated periodic signal in its round-trip to the target used to obtain the range value. The optical power is modulated with a constant frequency in terms of MHz range, so the emitted beam is usually a sinusoidal or square wave. After reflection from the target, the received signal is collected for calculating the distance and time of flight. The received signal can be demodulated to extract the phase information from it. Moreover, there is also another approach where sampling is done to receive modulated signal and mix it with the reference signal and then sample the resultant signal at four different phases. There are also ways where using an advanced modulated-intensity system become the solution [5]. They involve the multi-frequency techniques to extend the ambiguity distance without reducing the modulation frequency. Even though phase measurement may be coherent in some domains, the sensitivity of the technique remains limited because of the reduced sensitivity of direct direction in the optical domain.

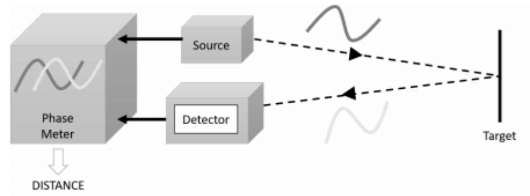


Figure 3 AMCW approach chart
(https://www.researchgate.net/publication/336173773_An_Overview_of_Lidar_Imaging_Systems_for_Autonomous_Vehicles/figures?lo=1)

Continuous Wave Frequency Modulated (FMCW) approach:

In this approach, the emitted instantaneous optical frequency is periodically shifted by varying the power applied to the source. The reflected signal is then mixed with the emitted source creating a beat frequency that is a measure of the probed distance. The source is normally a diode laser to enable coherent detection. The signal is then sent to the target, and the reflected signal that arrives to the receiver, after a travelled time and is mixed with a reference signal built from the emitter output. This type of detection method has the very relevant advantage to add on the capability of measuring not only range but also, on the same signal, the velocity of the target. This method takes advantage of the large frequency bandwidth available in the optical domain and exploits it to improve the performance of the range sensor [6]. The FMCW method provides a clear solution where values can be detected in picosecond range by performing frequency measurements in all the conditions.

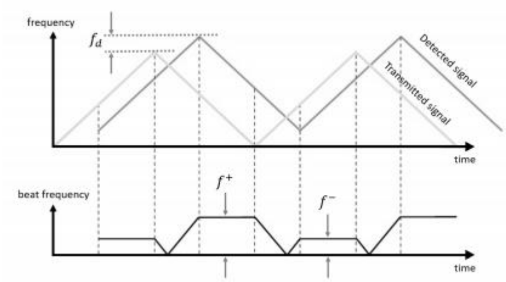


Figure 4 FMCW approach frequency (https://www.researchgate.net/publication/336173773_An_Overview_of_Lidar_Imaging_Systems_for_Autonomous_Vehicles/figures?lo=1)

Unbiased measurement approach:

A well-defined measurement method is required so that terminology and quantification remain consistent within the industry and can be clearly communicated among data producers and end users. Building on this concept and utilizing Delaunay Triangulation and Voronoi Diagrams in the quantification process, several problematic issues related to spacing and density values can be addressed. This includes homogeneity between theoretical acquisition statistics and the actuality of point distributions as they are affected by environmental variables like terrain, ground cover and instrument characteristics. The duality between Delaunay Triangulation and the Voronoi Diagram has an additional benefit of providing a compatible inter-relationship between spacing and density and facilitates additional data analysis from LiDAR datasets based on repeatable statistics. Delaunay Triangulation provides a method by which each LiDAR point can have a unique spacing and density value. The arrangement of the points is inconsequential to the triangulation so that theoretical and actual data are measured in the same way. As it applies to LiDAR data, the notion of disparate distance from point to point with respect to a long-track and across-track directions is eliminated.

Existing problems for measuring the 3D LIDAR data:

Weather conditions:

3D LIDAR will not work well in abrupt weather conditions. This is because the LIDAR is an optical device like a camera so if fog is heavy enough to block all light transmission, the data received would be less effective. However, 3D LIDAR will still provide valuable data in typical road conditions. They can be made effective by fusion of camera and radar to make it more effective.

Accuracy of data:

It is a concept that relates to whether there is bias or any change in the measurements. This is indeed different from precision which means the variation among the set of observations. On a broader perspective, it is impossible to have measurements that are very precise but inaccurate and very imprecise but accurate. There can also be problems due to the snow fall in certain conditions and in certain places. This will lead to relatively less accuracy in the results.

Uncertain data:

The uncertainty sums up the range of values within which the value of the measure falls within a specified level of confidence. 3D LIDAR uncertainty sometimes leads to misleading data and proper calibration must be made to avoid this error.

Conclusion:

Multilayer laser scanner are important sensors to obtain 3D information about the vehicle environment. By introducing the 3-dimensional LIDAR grid representation it was possible to take advantage of the multi-dimensional scanning technology of the laser scanner. It was shown that the spatial structure of obstacles could be extracted from the lidar measurements and thus providing valuable input for feature extraction. By taking the height of objects into account it was possible to distinguish between small objects on the road to be driven over and other more hazardous obstacles.

References

[1] An Efficient 3D Pedestrian Detector with Calibrated RGB Camera and 3D LiDAR, https://ieeexplore.ieee.org/document/8961523.

[2] 3D LIDAR-based ground segmentation with l1 regularization, https://ieeexplore.ieee.org/document/6896424.

[3] 3D Object Detection Based on LiDAR Data, https://ieeexplore.ieee.org/document/8993088.

[4] 3D Environment Measurement and Reconstruction Based on LiDAR, https://ieeexplore.ieee.org/document/8409759.

[5] New approach of imagery generation and target recognition based on 3D LIDAR data, https://ieeexplore.ieee.org/document/5274790.

[6] "Researchgate," [Online]. Available: https://www.researchgate.net/publication/336173773_An_Overview_of_Lidar_Imaging_Systems_for_Autonomous_Vehicles/figures?lo=1&utm_source=google&utm_medium=organic.

[7] "SHAI".