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Model based Verification and Validation of LiDAR sensor Aditya Madane¹, Nilesh Sakle²

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Abstract: This research paper presents the study of modelling and validating the results of simulation of LiDAR sensor with actual sensor data. The model can be further utilized for virtual testing of various ADAS functions. The virtual sensor is a physics-based sensor capable of emulating the real sensor. Initially an in-depth study of Velodyne VLP-16 sensor was carried out in order to parameterize the virtual sensor model. The sensor is modelled virtually in Gazebo simulation environment. Gazebo is used along with ROS (Robotic Operating Interface) in order to record the sensor data. Data conversion from sensor message format to Cartesian coordinates has been carried out. This was done in order to have a common format of actual and virtual data for validation. Four different objects were selected for validating the sensor data. The validation methodology is based on comparison of actual recorded data generated by Velodyne VLP-16 LiDAR and virtually generated data by the virtual LiDAR sensor model. The validation proves that the in case of static scenarios, the virtual lidar sensor model is 99 % accurate in measuring the range to the object. Although there is slight deviation from the actual value, it is in the acceptable limits.

Keywords: LiDAR sensor -Data Conversion, Modelling, Selection, Parameter Selection and Calculation, Scenario Generation, Virtual Data recording.

1. Introduction

The number of Advanced Driver Assistance Systems (ADAS) in future vehicle generations will increase steadily in order to support drivers by means of comfort and safety functions. Along with the ascent of ADAS functions, the challenge for developers to prove the safety and reliability of the overall system increases [10]. The risk for people and test equipment involved in potentially dangerous real-world test scenarios and the great efforts required to achieve reproducible results in real driving tests make an alternative test method necessary.

Whenever we consider virtual testing as an alternative to the conventional testing method, we need to consider the viability of the data produced by the virtual method. This dissertation focuses on that aspect. Autonomous vehicles use many sensors. LiDAR is an integral sensor used in autonomous vehicle. When we use a virtual sensor model, we need to be sure about validity of the data provided by the model, as the same data will be used for testing various ADAS functions.

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2. LIDAR SENSOR SELECTION

Initially a market survey was conducted and various LiDAR models were surveyed on the basis of range, Field of view, Azimuth and Vertical resolution, cost, availability, etc. Various LiDAR models by Velodyne, Ouster, Hesai, Robosense and LeiShen were studied. From the survey it was concluded that Velodyne VLP-16 Puck was the best sensor.



Figure 1. LiDAR Market Survey

This paper considers a scanning type LiDAR sensor manufactured by Velodyne which is typically used in the automotive sector. Velodyne LiDAR is a Silicon-Valley based LiDAR technology company who has been providing smart powerful LiDAR solutions for ADAS and Autonomous Vehicular Technology. Velodyne LiDAR's Puck is considered for virtual modelling. Velodyne LiDAR's Puck is one of lightest sensor - specially designed for applications that require a lower weight [17]. A compact footprint and an industry leading weight for a LiDAR sensor with high resolution makes the Puck ideal for UAV/drone and mobile applications in the areas of 3D mapping/imaging, inspection and navigation.Some important points regarding Velodyne VLP-16 are as mentioned below.

- Sensor uses array of 16 IR lasers paired with IR detectors.
- Each laser is fired approximately 18, 000 times per second.
- Measures up to 300,000 data points per second or double that in dual return mode.
- Thus, provides in real time a rich 3-D point data.
- Velodyne LiDAR sensor uses Time-Of-Flight methodology.

3. LIDAR SENSOR MODELLING

Sensor Model can be defined as the model that generates data similar to that of the actual sensor after digitization. The purpose of sensor model is to map three-dimensional world. LiDAR sensor model generates raw scan data. This section deals with virtual modelling of VLP-16 LiDAR sensor using ray tracing approach. Various phenomena associated with the actual physical sensor are considered. The modelling is done with help of two primary software's. They are Gazebo and ROS interface [14]. These platforms allow us with detailed modelling and visualization of the model respectively. The coding is done in XML (Extensible markup Language) language. The output can be visualized using RVIZ a visualization tool by ROS. This section provides us an insight into modelling approach used and detailed understanding of VLP-16 sensor.

Prior to the modelling process, we need to have a proper understanding about the physics of the actual sensor. In this study VLP-16 is the sensor that has been selected as the sensor to be modelled. The modelling process starts by creation of a basic Simulation description Format (SDF) model. This SDF model is an XML format file that describes the sensor. In this step the physical aspects of the sensor such as radius, height, number of links, etc. are modelled. The figure below shows the physical skeleton of the model. Based on the Velodyne documentation the virtual sensor model is created as combination of two links the bottom link and top link. The figure below represents top and bottom links inside the gazebo environment.



Figure 2. Geometrical model of LiDAR Sensor

In the second step alongwith physical properties the dynamic properties such as inertia and mass are added to the model. In absense of the dynamic properties such as inertia the model assumes certain random inertia values and cannot behave properly in the simulation environment which leads to erroneous sensor readings. Velodyne VLP-16 being a mechanical rotating type of sensor, a reference axis is provided along which the sensor can rotate freely.



Figure 3. LiDAR sensor model after application of inertia

On careful analysis of the rotating type of sensor, it was found that, the most common type of the joint between two links was revolute type of joint. In gazebo there is a provision to specify such rotary type of joint. In order to specify the joint, bottom link was specified as parent link (stationary link) and top link was specified as child link (rotating link). The rotation of the virtual sensor model was checked by applying different speeds of rotation to the sensor model. After successfully completing the rotation test, the main element inside the sensor was added. This element was the ray sensor. Ray sensor had 2 elements within itself i.e., scan and range. Scan elements houses information about horizontal and vertical beams. Range element consisted of information such as actual minimum and maximum range of the sensor. Further the physical appearance of the sensor was enhanced with the help of mesh files of the sensors



Figure 4. LiDAR sensor model with Velodyne mesh

The modelled sensor does not show any error, but this behavior is not analogous to the actual sensor. In case of actual there is always presence of noise. In order to match the actual and virtual output a gaussian noise model has been added. This is a prebuilt model available with the gazebo model libraries. This proved as a good approximation of the actual sensor noise.

4. PARAMETER SELECTION AND CALCULATION



Figure 5. Physical layout of VLP-16 sensor

Inertia Calculation:

In the 1st step of sensor modelling our model lacked inertia as well as mass, this was specified with the help of inertial and mass tags inside the SDF file. The mass was equally divided into the two links. Inertia was calculated with the help of conventional inertia formulae for cylinder. The inertia values are similar for both top and bottom links. The table below represents the inertia for top and bottom links of the sensor



Figure 6. Inertia of a cylinder

Table 1. Inertia of the sensor			
I _{xx}	$5.524*10^{-4}$	Kgm ²	
		0	
I _{yy}	3.206*10 ⁻⁴	Kgm ²	

I _{zz}	3.206*10 ⁻⁴	Kgm ²

Azimuth resolution and Number of Points:

The firing timing of the sensor is fixed at 55.296 µs per firing cycle [12], this changes the angular resolution of the sensor, if RPM is varied. By changing the RPM in the equation below we have calculated the azimuth resolution and number of data points for different rotation speed. Only Horizontal resolution is affected by change in the rotation speed of the sensor. Vertical resolution depends upon the geometry and arrangement of the laser sources inside the sensor; hence it is always constant. In our case we found out that we had 16 lasers stacked one above the other with a vertical resolution of 2 deg. Based on this information we were able to calculate the total number of data-points.

Azimuth Resolution = $600 \text{ rpm} * (1/60 \text{ min/sec}) * (360 \text{ deg/rev}) * 55.296 * 10^{-6}$

Number of Horizontal Points = 360/Angular resolution

RPM	Resoluti	Number	Numb	Total
	on (deg)	of	er of	Data
		Horizont	Vertic	Points
		al Data	al	
		Points	Data	
			Points	
300	0.1	3600	16	57600
600	0.2	1800	16	28800
900	0.3	1200	16	19200
1200	0.4	900	16	14400

Table 2. Resolution, Data Points and RPM correlation

Table 3. LiDAR sensor Parameters

Number of lasers	16	
Horizontal	0 1-0 4	Deg
resolution	0.1 0.1	Deg
Vertical	2	Deg
resolution	1	
Horizontal		
Field of	360	Deg
View		

Vertical	20	5
Field of	30	Deg
View		
Range	100	m
Wavelength	903	Nm
Transmit	31	W
Power		
Weight	0.83	Kg
Radius	0.0516	m
Height	0.0717	m

5. SCENARIO GENERATION

Validity of a senor model cannot be proven generally. Hence sample validity is used as a measure. Sample validity can be proven with the help of scenarios [6]. In this paper, different scenarios are created based on actual recorded data [18].

These scenarios are modelled in gazebo by using pre-existing object models in its library. The recorded data has several static objects during its initial and final frames. These objects, there positions were identified. This data proved a reference for modelling and creating different scenarios. Each scenario consists of individual object and the sensor which records the data. Based on the recorded position relative to sensor, object models were placed exactly at the same location as that of the actual data. Four different objects were used for validating the model. The object and its distance relative to the sensor are as follows.

J	
Object	Actual
	Distance
	(m)
Pedestrian	3.3094
Van	18.4032
Tree	3.5264
Car	6.6145

These different objects were identified from the actual recorded data available at Velodyne official website







Figure 7. Scenario Modelling inside Gazebo environment

6. VIRTUAL DATA RECORDING

The entire sensor modelling and scenario generation can be successfully carried out in Gazebo simulation environment. But recording the sensor data is not possible inside the Gazebo environment. ROS is used as intermediatory software to visualize and record the output sensor data from the virtual sensor model. ROS has visualization RVIZ that is used for visualising the point cloud data from the sensor.

The output from the sensor is recorded by using rosbag record command inside the terminal window of Linux based operating system [15].

source /opt/ros/noetic/setup.bash rostopic list rosbag record -O subset /velodyne_points /velodyne_points2

7. LIDAR DATA CONVERSION

The data recorded by the actual sensor is recorded in pcap format. This is a proprietary data-type from velodyne. The advantage of this data-type is that we are directly able to access usable data on the go with the help of veloview. We are presented with already processed data.

But actually, the data is recorded as a PointCloud2 message. This message is further processed to obtain the pcap file. The actual data contains following information-

- Timestamp.
- Azimuth
- Distance
- Intensity
- Vertical Angle.

Similarly, the virtual data was analysed. Virtual sensor uses a plugin which converts and records the raw data as velodyne_points packet. The velodyne_point packet contains sensor_msgs/PointCloud2 Message within itself. This data needed to be converted into usable format i.e., cartesian co-ordinates system. There are various approaches of converting this data. Most notable of those are with the help of python3 and MATLAB.

In this study, MATLAB script along with ROS toolbox was used as a viable solution to convert and de-serialize the data into X, Y & Z coordinates [17]. MATLAB script to convert the lidar data into cartesian co-ordinates is as follows.

Bag = rosbag('ROS.bag'); Bag.AvailableTopics A = select (Bag, 'Topic', '/velodyne_points2'); Ptcloud = readMessages(A); xyz = readXYZ(Ptcloud{2,1});

8. RESULTS

The basic principle for validation of the sensor model was direct comparison of the data from a real-world test drive to virtual data generated by the sensor model in a virtual environment [5]. Static validation means the sensor data is recorded in a non-moving static environment [8]. Static validation ensures maximum comparability between the real and virtual world [3]. The validation metric selected for validating the data from the sensor model was comparison of range histograms [1]. Virtual Data was recorded for various frames of sensor. The range (distance) values were used as basis of comparison between 2-point clouds. These Histograms are basically frequency plots used to compare the range variability and accuracy of the model in case of static scenarios. The actual data for twenty-one different static frames was analyzed. Similarly, the virtual data was recorded for twenty-one Point cloud messages. This data was then converted in a histogram to examine the variability in the distance measurement. Histograms were plotted for actual and virtual data for each of the objects and these were compared accordingly.



Figure 8. Simulation result - Range Histogram for Van



Figure 9. Actual Data - Range histogram for Van



Figure 10. Simulation result - Range Histogram for Car



Figure 11. Actual data - Range Histogram for Car



Figure 12. Simulation result - Range Histogram for Tree



Figure 13. Actual data - Range Histogram for Tree



Figure 14. Simulation result - Range Histogram for Pedestrian



Figure 15. Actual data - Range Histogram for Pedestrian

Object	Actu	Simula	Differe	Percent
	al	tion	nce	age
	Dista	Distan		Error
	nce	ce (m)		
	(m)			
Pedestr	3.309	3.3299	0.02	0.6191
ian	4			
Van	18.40	18.405	0.0018	0.0097
	32			
Tree	3.526	3.514	0.0124	0.356
	4		36	
Car	6.614	6.6169	0.0023	0.0355
	5		54	

Table 5. Quantitative comparison of actual and simulated data

The above table illustrates that the lidar model can satisfactorily replicate [2] the actual sensor behavior in terms of recording the distance to an object. The results are well within the target. It reflects that the Gazebo model is accurate and replicates the results upwards of 99% in case of static objects. Due to no relative motion between the lidar and the object we were able to replicate the lidar behavior to such an extent. The error may amplify for dynamic conditions.

9.CONCLUSION

Velodyne VLP-16 model was successfully modelled using Gazebo environment. ROS was used as an intermediatory to successfully record data from the virtual sensor model. The data recorded from virtual and actual environment had inherent differences in it. The virtual data was successfully converted from a bag format to cartesian co-ordinates with the help of MATLAB ROS Toolbox. This provided us with a common platform for analysis of both these data. Finally, a two-step validation approach was developed with help of statistical tools such as range histogram. This approach was tested using four different static scenarios. The uncertainty in the range measurement was calculated with the help of histograms. Analyzing the quantitative results [2], it was found out that larger objects such as cars, vans had less uncertainty in the range measurement i.e., 0.0097 and 0.037 %. On the other hand, smaller objects such as trees and pedestrian had larger variation i.e., 0.356 and 0.6191 %. The variation in case of smaller objects was caused due to distortion of point clouds.

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