Self-generated 3D point cloud with raw data from FMCW radar

DAMON KAEWBORISUT, University of Twente, The Netherlands

Point clouds are used everywhere, and they have become vital in numerous applications such as robotics, autonomous vehicles, and virtual reality. It is possible to generate a point cloud with a Frequency Modulated Continuous Wave (FMCW) radar. There are two ways: On-chip data of the point cloud from the radar or transforming the raw data of the radar into a point cloud externally of the radar. In this paper, I will focus on the latter part by recording the raw data with an FMCW radar and applying pre-processing steps on the raw data to find the points. To validate my implementation, my generated point cloud will be compared to the Robot Operating System (ROS) provided by Texas Instrument, which shows the point cloud by receiving on-chip data from the radar. The goal of this paper is to research the possibilities of improving the hardware limitations of the radar by doing computations outside of the radar.

Additional Key Words and Phrases: point cloud, pre-processing steps, FFT, FMCW radar

1 INTRODUCTION

We have two eyes for two reasons: A wider field of view and most importantly depth perception. Our eyes are able to perceive the depth of objects. The brains use the images of both eyes to estimate the distance of objects and create images you see. Surprisingly, the same method can also be applied to FMCW radars, where multiple receivers with data can estimate the depth and detect where the targets are.

One of the complex applications of the FMCW radar is point cloud generation, which can be considered as a rich, three-dimensional dataset, each representing a precise location in space. These digital representations allow us to capture and analyze the geometric characteristics of real-world objects and environments. The applications of point clouds are vast and span various industries. In the field of robotics and AI, point clouds enable precise object recognition, scene understanding, and autonomous navigation. Furthermore, point clouds find applications in virtual reality, augmented reality, and environmental monitoring. Thus, point clouds are essential in the research field.

There already exist methods for creating point clouds. With an FMCW radar, you have two choices for reading data: reading raw data directly from the ADC or reading the processed data from the serial port. the latter gives the points in the point cloud, with their x-y-z coordinates, velocity, and signal strength. But there are some limitations with this method: There are hardware limitations with the small FMCW radar, which could reduce the quality and quality of the generated point cloud by using less computational algorithms. Therefore, I suppose a method for only reading the raw data from the radar and doing pre-processing steps on an external host (PC or laptop).

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For this paper, I will be answering the following research questions and sub-questions:

- Is it possible to improve the number of points clouds and quality of the point cloud by self-generate point clouds externally from the raw data?
  - Which one is better? In terms of the number of PCs (average over frames) or having less or higher noisy points?
  - Why and how can we solve it and improve our point cloud generation algorithm?
- How do the key parameters for both ROS and raw data method for point cloud affect the quality and quantity of generated point clouds?
  - What variables and parameters can we configure for changing the number of collected point clouds?
  - What are the trade-offs and compromises for changing the parameters?
  - Which parameters give us the highest/lowest number of points? For which applications are they practical?
  - Is having a higher number of PCs equivalent to having more valuable points (points reflected from the object, not noisy points or points reflected from the static objects)?

I will answer this question by conducting two experiments with the same measurement setup but with different methods:

(1) Generate point clouds by using the Robot Operating System (ROS) with the processed on-chip data
(2) Generate point clouds by applying post-processing steps from the raw data of the FMCW radar

By exploring the different configurations for both methods, I will be able to observe the changes in the quality and quantity of the point cloud.

2 RELATED WORKS

There is already research done on creating point clouds. One paper used the FMCW radar for Human Activity Recognition by creating point clouds and Deep Recurrent Neural Networks. The raw data of each virtual channel is transformed into Range-Velocity maps, to calculate the Azimuth and Elevation angles of the target. Because they used four IWR1443BOOST radars, they had a total of 192 virtual channels, which improves the angle resolution (the minimum angle to distinguish two objects) significantly [6].

Another paper uses the on-chip data of the radar for Human detection and tracking with multiple radars. They used the out-of-box image provided by TI for the on-chip data processing chain, which returns data packets of detected objects a front of the radar with x-y-z coordinates and velocity. With multiple radars comes extra challenges: Synchronization between radars, signal interference and combining all the data. Fortunately, they implemented a framework to overcome the challenges and can even be performed in real-time for tracking humans [1].

the last related work uses point clouds to detect Patient behaviour in real time. Both the point clouds and the Doppler feature (time-velocity map) of each point will be used to classify the movements of the patient with a Deep Convolutional Neural Networks (CNN) model. Because the behaviours of the patient involve movement, the Doppler feature is a must [5].

The rest of the paper will be as follows: First some background knowledge about the topic, then the methodology of the experiment, the results, the discussion and lastly, the conclusion.

3 BACKGROUND

3.1 Radar principles

For creating point clouds, the FMCW radar IWR1443BOOST made by Texas Instrument (TI) will be used for recording data of the test subject, which has three transmitters (TX) and four Receivers (RX). Thus, it is possible with Multiple Inputs and Multiple Outputs (MIMO) to create up to twelve Virtual channels [3]. This will be useful for the angle estimation, which will be explained in the next section 3.2.

The radar sends a chirp (whose frequency increases over time) through the TX, then the signal reflects onto a target and eventually the reflected signal will be picked up by the RX. Lastly, the TX and RX signals are combined to produce an intermediate frequency (IF) signal, which contains information about the time delay between TX and RX. Within each IF signal, it contains n Analog-to-digital (ADC) samples. the radar can be configured to send a frame of multiple chirps in a row, which is a 2D matrix (n chirps by m ADC samples). Lastly, the last step is to combine all the 2D matrices of each virtual channel to make a 3D matrix (a virtual channels by b chirps by c ADC samples), With the 3D matrix, the range, velocity and both azimuth and elevation Angle can be determined for the test subject of the radar [4]. When a target is located within its respective range and angles, The Exact point could be determined for the point cloud.

3.2 Radar configurations

The radar has numerous configurations which can influence max range, max velocity, or angle resolution. In this thesis, range resolution and angle resolution are essential because the FMCW radar must detect targets as much as possible to create a big dataset for the point cloud. Because my test subject is standing still, the configuration for velocity is non-essential for the point cloud generation.

The chirp is characterized by a start frequency (F_c in Hz), bandwidth (B in Hz), duration of the chirp (T_c in seconds), and the slope of the chirp (S in Hz/s) captures the rate of change of frequency.

Range resolution (d_{res}) determines the minimum distance between two objects, such that the adjacent targets are distinguishable. The formula for the range resolution is as follows:

$$d_{res} = \frac{c}{2B} \tag{1}$$

So, for a lower range resolution, the radar only needs to increase its bandwidth and the bandwidth is depending on the T_c and S ($B = T_c * S$).

Angle resolution is the smallest angle between two close point-like objects that can be seen as just separated. The formula for the angle resolution is as follows [3]:

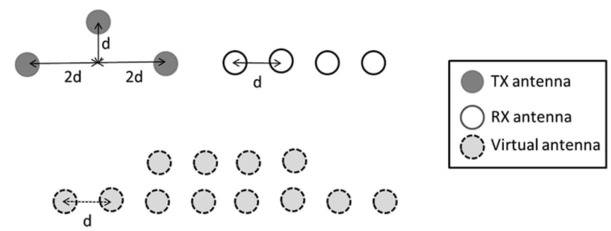


Fig. 1. The 2D antenna MIMO array

$$a_{RES}(\theta) = \frac{\lambda}{Ndcos(\theta)} * \frac{180}{\pi} = \frac{2}{N} * \frac{180}{\pi} \tag{2}$$

where θ is the angle at which the objects are present, λ is the wavelength of the signal used, d is the distance between virtual channels and N is the number of virtual channels that align in either the azimuth or elevation axis. Because $d = \lambda/2$ and the assumption is $\theta = 0$ (target is a front of the radar), the angle resolution will be simplified to $\frac{2}{N} * \frac{180}{\pi}$, which is in degrees. So for our implementation, I have 8 virtual channels for azimuth estimation and the angle resolution will be around $\frac{2}{8} * \frac{180}{\pi} \approx 14.3$ degrees. the elevation resolution will be pretty high because I am only using two virtual channels. elevation resolution is around $\frac{2}{2} * \frac{180}{\pi} \approx 57.2$ degrees.

For angle resolution, it is important to know which virtual channels will be needed for azimuth and elevation estimation. on Figure 1, the 2D antenna MIMO array for radar is shown, where the horizontal axis on the picture is the azimuth and the vertical axis is elevation. As mentioned previously, the row with eight virtual channels will be used for the azimuth estimation, and the first column with two virtual channels in the vertical axis will be used for elevation estimation.

3.3 FFT

Fast Fourier Transform (FFT) algorithm is used to convert a digital signal (x) with length (N) from the time domain into a signal in the frequency domain since the amplitude of the ADC samples is recorded based on its changes through the whole chirp versus the frequency at that the signal appears [8]. FFT can be used for range, velocity and angle estimation. Then, FFT will be applied on the axis of 1 frame of multiple virtual channels (a virtual channels X b ADC samples X c chirps), Which corresponds to range (ADC samples), velocity (chirps) and angle axis (Virtual channels) [7]. The frequency domain of the FFT algorithm output has negative and positive frequencies, thus it is possible to estimate negative and positive velocities and angles.

3.4 ROS

Robot Operating System (ROS) is a flexible framework for writing robot software. It is a collection of tools, libraries, and conventions which includes a TI mmWave Out-of-Box demo for generating the point cloud. The demo will be flashed into the radar such that the

Fig. 2. Me standing in front of the radar

radar returns on-chip data of the point cloud. The ROS configurations can be changed for user preference, such as the chirps, CFAR configurations or enabling static clutter removal.

4 METHODOLOGY

4.1 experimental setup

The test subject, which is me, will be placed in a room without any obstacles and two meters a front of the radar. For the point cloud generation, I will be in four kinds of postures: standing, sitting, spreading arms, and spreading arms on knees. First, two hundred frames of each activity will be recorded. After recording all the activities with the radar, the gathered data of each frame will be generated into a point cloud from an external host outside the radar by applying post-processing methods. In table 1, the radar configurations are shown for the radar.

For the ROS, the measurement setup will be done in the same room. And by using the mmWave Demo Visualizer provided by TI, the same radar parameters can be created for the ROS configurations such as the max range and range resolution. Then, multiple different ROS configurations of their point clouds will be compared to each other to observe the effects on the point clouds. the observed parameters are CFAR threshold 4.2.3, peak grouping(for a cluster of detected neighbouring points only the point with the signal strength is shown), and multiple Object Beamforming (This feature allows the radar to separate reflections from multiple objects originating from the same range/Doppler detection).

4.2 Signal processing methods

The radar is capable to detect targets with their Range, velocity, and Angle. Although, signal processing must be applied to the data for detecting the test subject. One of the related works [1] proposed post-processing steps for acquiring the x-y-z coordinates for the points, which includes a Range map, Range-Doppler map, CA-CFAR and Range-angle map. After acquiring the points with their respective range and Angles, the point cloud can be generated.

Start frequency	77GHz
ADC samples	256
Chirp slope	65.998 MHz/μs
Bandwidth Slope	1798.92 MHz
Sample rate	5000 ksps
Chirps per frame	128
Frames	200
Max range	5.63 m
Range resolution	4.4 cm

Table 1. Radar Configuration

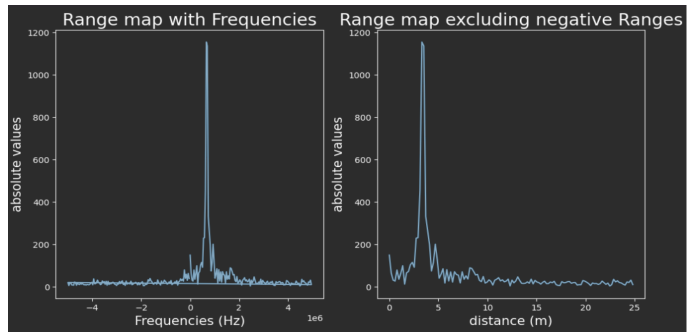


Fig. 3. Range map of 1 chirp with frequencies and distances

4.2.1 Range map. With one chirp, it is possible to plot the Range map, which shows the peaks where the target is in the range compared to the radar. Every ADC sample of the chirp has been captured at a different frequency because the chirp is linearly increasing in frequency. after applying 1D range FFT on all the ADC samples, it will return the Frequency domain from negative to positive frequencies for the IF signals as shown in Figure 3. every frequency corresponds to a range bin, by using the equation with corresponding Frequency slope (S) and speed of light (c) [4]:

$$d = \frac{IF * c}{2 * S} \tag{3}$$

This means that negative frequencies give negative ranges. Because the positive ranges are the only ranges of interest, we only need to focus on the positive ranges. By looking at Figure 3, There is a peak around 4 m. So, this chirp detects an object around this range.

4.2.2 Range-Doppler map. The Range-Doppler map gives not only information about the velocity of a target, but it could also distinguish targets with the same range, but different velocities. the Range-Doppler map uses a frame as data (n ADC samples X m chirps) to apply 2D FFT. First, apply Range FFT on all the chirps with their samples (Range-axis), and then apply Doppler-FFT on the samples between chirps (Doppler-axis). Again, the velocity is calculated by comparing the phase differences between two received signals. by applying FFT along the Doppler axis, it shows the peaks for the

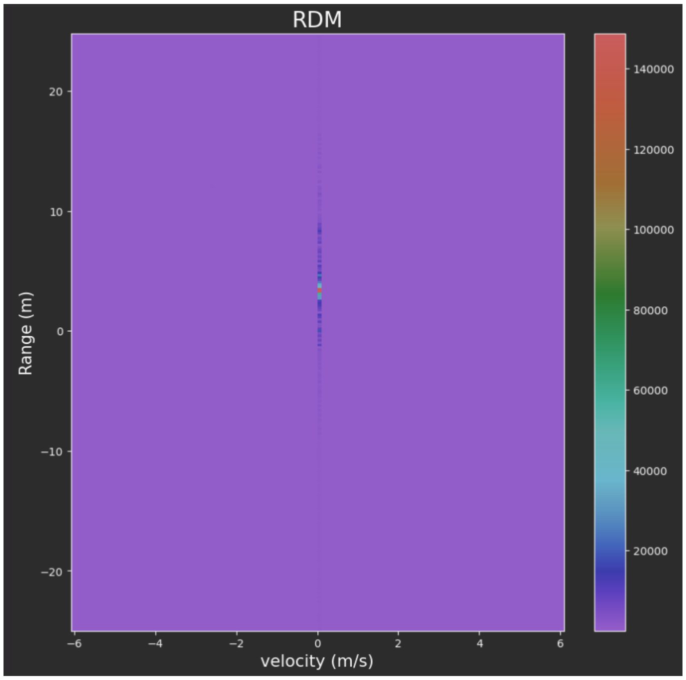


Fig. 4. The Range-Doppler map of 1 RX

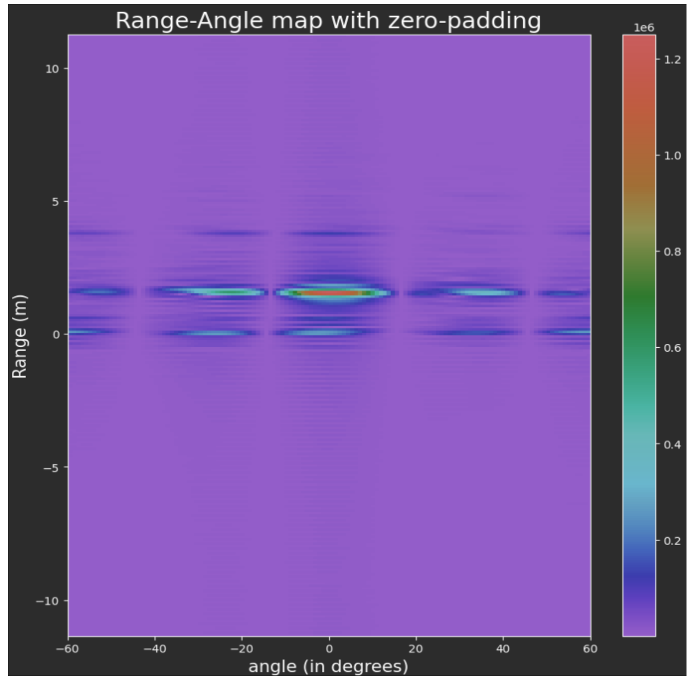


Fig. 5. The Range-Angle map at candidate Velocity

detected velocity. The Range-Doppler map takes all the chirps into account for range estimation, when observing the Range-Doppler map in Figure 4, it is not surprising that no peaks have velocity, and the observed peak of the range is around 3 meters.

4.2.3 *CA-CFAR.*

To detect the peaks, a Cell Averaging Constant False Alarm Rate (CA-CFAR) will be used [2]. The noise level will be calculated around the Cell Under Test (CUT) by taking the average Training cells. With CA-CFAR, it will exclude cells adjacent to the CUT (Guard cells) to avoid corrupting this estimate with power from the CUT itself. Then by adding the CFAR offset (in DB) to the noise level, I have the threshold for the CUT. If the CUT exceeds the threshold, then the CUT is a detected target with its respective Range and Velocity bin. When applying CA-CFAR on Figure 4, one of the candidates has Range and Velocity bins of 3.320 meters and 0.048 m/s. Which will be used for calculating the azimuth and elevation angle with the Range-Angle map.

4.2.4 *Range-Angle map.*

When aligning the virtual channels along the azimuth or elevation, it is possible to estimate the angle of the target. First, all Range-Doppler maps are put together in a 3D matrix (a virtual channels X b chirps by c ADC samples). Secondly, the results from the CA-CFAR will be used for plotting the Range-Angle map. For the 2D matrix at the candidate Velocity bin (ADC samples X virtual channels), FFT with zero padding will be applied on the angle axis as shown in Figure 5. Lastly, the maximum of the array of the candidate Range bin in the 2D matrix with the Applied FFT will determine the angle estimation.

4.2.5 *Point cloud creation.*

When all targets are calculated with their respective range and Angles (*r, azi, ele*), then the 3D cloud can be made with respect to the radar with its height *h*. By using the Spherical coordinate system, the Cartesian coordinates for the target will be calculated as follows:

- $X = r * sin(ele) * cos(azi)$
- $Y = r * sin(ele) * sin(azi)$
- $Z = r * cos(ele) + h$

4.3 ROS

As mentioned in the introduction, I will be using the ROS to compare the point clouds to see if the point cloud works and if my implementation is valid, because there is a possibility that both my implementation and the ROS give invalid point clouds because of external factors (radar malfunctioning, interference). The ROS provides a radar configuration for running the demo and plotting the point cloud, which will be used for this paper.

5 RESULTS

For raw data method, one hundred frames were recorded per activity and all points found in each frame were has its own point cloud. Every frame detected around twenty points. In Figure 6, the point clouds for one of the activities *standing* is shown with Range detection Threshold 15 DB with a 3D view, front view and top view.

For the ROS, 10 frames of point clouds were used as a reference for showing a successful point cloud generation with an FMCW radar in Figure 7 with the disabling peak forming and Range detection threshold of 15 DB.

In both methods, the color of the points is determined by the depth distance, where short ranges are dark green and the further the distance in the depth axis, the lighter the color becomes. Also the red dot (X=0, Y=0, Z=1 meter) indicates the radar position and the white plus marker (X=0, Y=2 meter, Z=1 meter) indicates me standing in front of the radar.

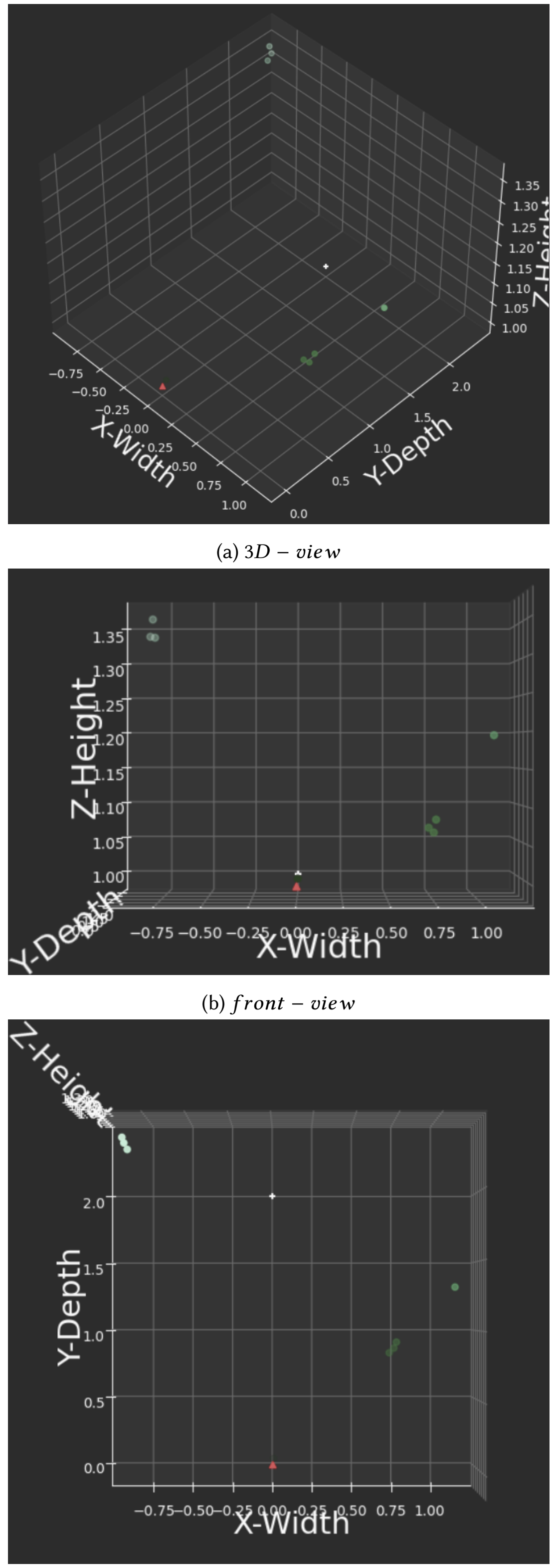
With a range detection threshold of 15 DB for both the ROS and the raw data method, I achieved on average 50 points and 8 points respectively. To find out how many points are around me. I will consider all the points around me with x ± 0.5 meters, y ± 0.5 meters and z ± 1 meter. As mentioned before, there are almost no points found around me in the raw data method, whereas ROS detects on average 10 points.

6 DISCUSSIONS

The point cloud that my implementation created, did not show any points around the range of interest (2 meters a front of the radar). and detected an enormous amount of noise and background objects. When observing the point cloud of ROS, ROS did 'detect' and 'see' me in front of the radar. One of the factors could be that there is multi-path propagation (signals reaching the receiving antenna by two or more paths) involved with the signals. Instead of the signal transmitted, bounces of the test subject and Signal received, it involves an extra bounce from transmitting, bounces of the wall, bounces of the test subject, and received. This could create signal interference and phase shifting of the signal. To reduce the amount of signal interference, the ideal scenario would be outside in an open space with no ceiling, walls, or other objects. Also, for my implementation, a low angle resolution is a must to distinguish two objects from each other (left and right arm). But the angle resolution for especially the elevation resolution (57.2 degrees) is high. To overcome this challenge, it is possible to lower the resolution by using more radars and therefore have more virtual channels [6]. Lastly, the angle estimation only considers the highest peak in the Range-Angle map for a certain range. It is still possible that multiple points have the same range and speed, but different angles. My method will only choose 1 point and exclude the other potential points. For future work, it is possible to create an Elevation-Azimuth map[6]. With this map, a similar algorithm will be applied such as CFAR to detect multiple points in the Elevation-Azimuth map. But this will increase the computational resources.

There are multiple parameters to change the quality and quantity of the point clouds. For both methods, the range detection threshold for CFAR is one of the key parameters for creating point clouds. Because by lowering the threshold, more points will be detected, but those points will have a lower signal strength, which could give more points of the object or more background noise. It is also possible to change the CFAR configurations, such as the number of guard cells and train cells. By changing the threshold to 9 DB, the number of points will increase to 64 and 70 for ROS and raw data methods. Also with a lower range resolution, the radar will be able to 'distinguish' objects with a smaller marge and see more objects. So, it is important to increase the Bandwidth of the chirp with the number of ADC samples, sampling rate, and frequency slope.

What distinguish the raw data method from the ROS is it has extra post-processing steps. Peak grouping is one of them. It only shows the point with the highest signal strength for a cluster of detected neighbouring points with range and/or velocity grouping. It is not

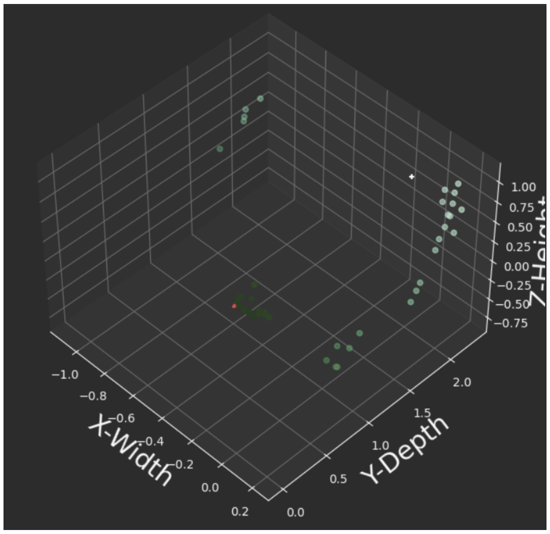


(a) $3D - view$

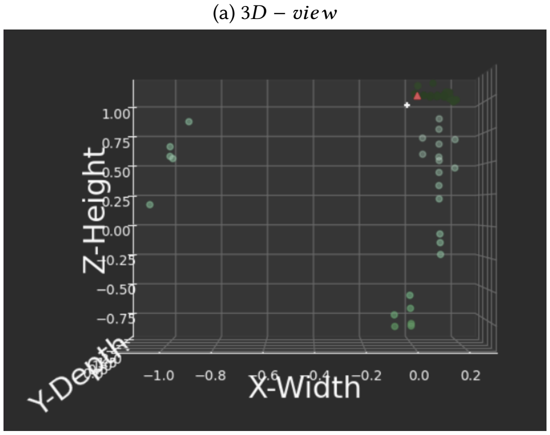
(b) $front - view$

(c) $top - view$

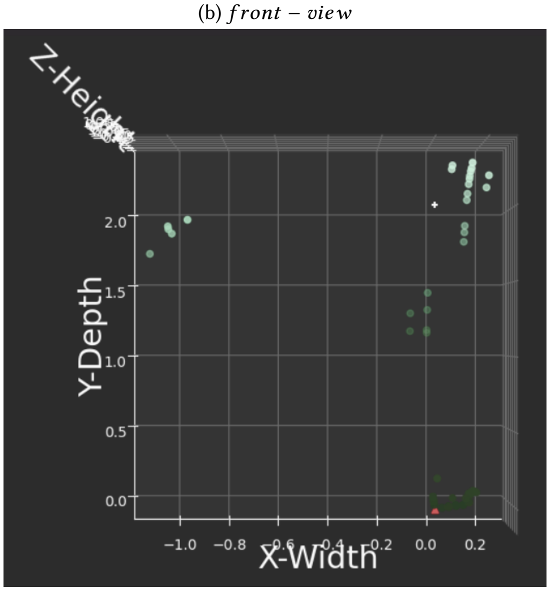
Fig. 6. Point cloud for standing with raw data method



(a) $3D - view$



(b) $front - view$



(c) $top - view$

Fig. 7. Point cloud for standing with ROS with 15DB

surprising that the number of points will be reduced, but it could be used for finding the number of distinct objects. also has Multiple Object Beam Forming (MOBF). This feature will separate reflections from multiple objects with the same range/Doppler Detection. The second highest peak in the angle FFT will be a candidate point if it exceeds the threshold, which is for ROS the half of the highest peak. This could potentially double the points of the detected points from CFAR and detect multiple points with the same range and velocity. Lastly, static clutter removal (removes all the points at zero velocity bins) can be applied on ROS, but it will most likely remove all the points for my application because I'm standing still in front of the radar. Therefore, it could be used for applications where movement is involved to remove the noise of static objects.

To obtain the highest number of points, the range detection threshold must be as low as possible, enable MOBF, and disable peak forming. This will show points from any kind of object that also have a reflection with low signal strength. This can be applied to scene orientation. For the lowest amount of points, the range detection threshold must be as high as possible to see detect the desired objects, enable peak forming, and disable MOBF. This will only detect the points with the highest signal strength. Applications such as object detection can use these parameters.

When comparing the raw data and ROS method, the ROS is significantly better than the raw data method, even though the number of points of the raw data with threshold 9 DB is higher than ROS. The raw data method does not have any points around the test subject, while ROS does detect the test subject with multiple points around it. Thus, ROS is far better than the raw data method. The raw data method can be improved by using different CFAR thresholds to ensure that most of the points are the test subject. The raw data method can also make use of the MOBF to increase the number of points.

7 CONCLUSIONS

In this paper, we have seen an approach to create point clouds from the raw data of an FMCW radar, which could overcome the hardware limitations of the radar. From previous works [5][6], it is possible to create correct point clouds from raw data, but some factors must be taken with extra care such as angle resolution, signal interference and angle estimation techniques. To improve the raw data method, using multiple radars could be used for improving the resolution, other angle estimation techniques and MOBF to increase the number of points in the point cloud.

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