ENGIN 492 <Senior Design Project II>

Engineering Department

University of Massachusetts Boston

Semester - Spring 2021

Instructor – Dr. Tomas Materdey

Fast mmWave RF 3D-Object Reconstruction in Low-Visibility Environment via UAV Platform

By

Zhuoming Huang

Alinson Sanquintin

Customer Mentor/Technical Manager: Dr. Honggang Zhang

Fast mmWave RF 3D-Object Reconstruction in Low-Visibility Environment via UAV Platform (May 2021)

Zhuoming Huang, *UMass Boston*, Alinson Sanquintin, *UMass Boston*

***Abstract*—This report introduces the design, implementation, and evaluation of a method of fast 3D-Object Reconstruction in low-visibility with mmWave RF (radio-frequency) sensing via UAV Platform. The design integrates the features of the sensing capability of a mmWave radar sensor in low-visibility environment (e.g. smoke, fog, mist, haze, etc.), and deep neural networks trained with a depth camera and sparse radar sensing data. A preliminary design of a mounting platform is also developed for integrating the radar and depth camera sensors with an UAV that can access different environments with high flexibility.**

I. Introduction

SIMULTANEOUS Localization and Mapping (SLAM) is a technology for localizing and tracking objects in an unknown environment while constructing a map of it simultaneously. While conducting the SLAM, we would like to have a carrier with high flexibility that allows us to use our equipment in as many situations as possible. Unmanned vehicles and automation are widely used in auto-driving, exploring unknown and dangerous places, localization and mapping. An Unmanned Aerial Vehicle (UAV) or a drone with an advantage of not being restricted by most environments such as rugged or high places that are problematic to an Unmanned Ground Vehicle (UGV), is preferred for such a mission. Its ability of moving freely in a 3D-Space space allows it to cover a large area with ease.

Dr. Honggang Zhang at the Department of Engineering, University of Massachusetts Boston, is our custom mentor (CM) as well as technical manager (TM). He would like to have a 3D-object reconstruction system to perform SLAM on an UAV. The system should have millimeter-wave (mmWave) radars and 3D cameras for data collection, and a software or an algorithm for data processing. Potentially, it should also provide an integrated user interface for easy configuration. We propose a system that integrates sensor data from both radars and cameras, processes it on a GPU computing platform for estimating coordinates of objects in a space, and outlines the shapes of these objects. It can be used in any platform, either mobile or stationary. Our system will have the following three features: it can accurately reconstruct 3D images of a scene with an error about one centimeter; it is portable, specifically small and lightweight, to be carried by a quadcopter; it uses low-cost but accurate sensors.

II. Problem Statements

A. Explorations and Rescues in High-risk Area

In the scenes of fire with smoke and toxic gas, or of dilapidated buildings that could collapse, it is dangerous for human beings to access these areas to explore or rescue. Finding a safe route in those environments is difficult due to low visibility, and any time delay can potentially cost lives in those rescue scenes. Using a 3D-object reconstruction system via an UAV platform allows passing around obstacles while mapping the scenes. It will help saving time and reducing risk if we know the locations of objects we are looking for or people needed to be rescued, with the safest and shortest route.

B. Efficient and Affordable Managements

Beyond the factors mentioned above, we are actually seeking for an affordable method to perform efficient managements for risks, strategies, and operations. A 3D-object reconstruction system can reduce time and cost by easily visualizing and monitoring a large area which requires either a few labor and resources with plenty of time, or a little time with significant labor and resources. The cost of operating and maintaining such a system can be very low.

C. Non-intrusive Monitoring for Public Safety

In a global crisis like the outbreak of Covid-19, people need to wear masks and keep a social distance to avoid being infected and further spread of the virus. Monitoring whether people are following those polices to ensure the public safety becomes necessary, especially in areas like beaches, parks, and shopping malls. However, the execution of these policies relies on self-discipline and difficult to be monitored. A 3D-object reconstruction system can reconstruct these scenes for monitoring and tracking the distance among objects. With UAV's advantage of reaching a high place, the map can easily cover a larger area. In addition, it also provides a basis for detecting and recognizing objects like human beings and their masks.

April 18th, 2021. This work was supported in part by the Department of Engineering, University of Massachusetts Boston.

Zhuoming Huang is with the Department of Engineering, University of Massachusetts Boston, Boston, MA 02125 USA, senior student majors in Computer Engineering (e-mail: Zhuoming.Huang001@ umb.edu).

Alinson Sanquintin is with the Department of Engineering, University of Massachusetts Boston, Boston, MA 02125 USA, junior student majors in Computer Engineering (e-mail: A.Sanquintin001@ umb.edu).

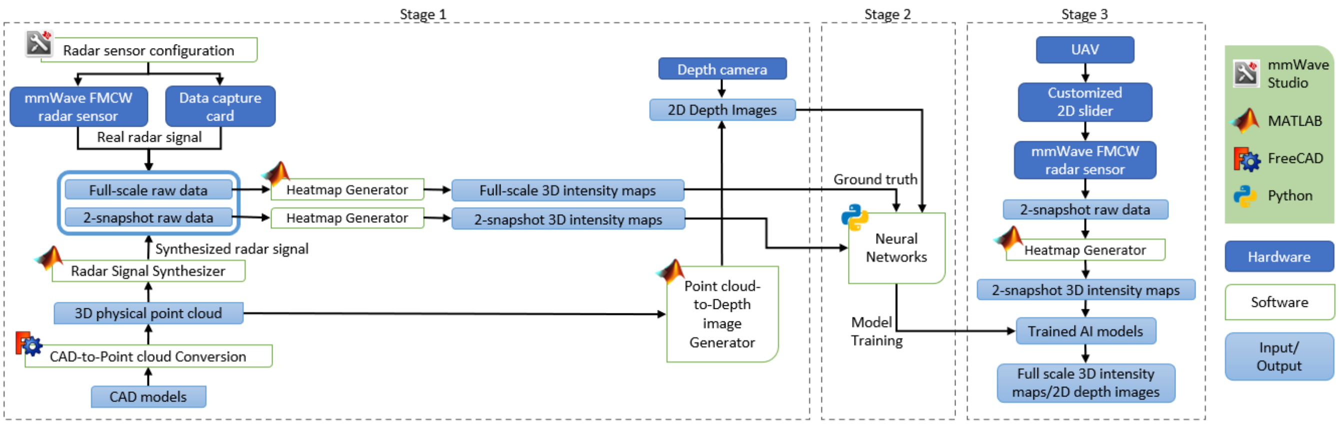

Fig. 1. System architecture block diagram.

III. System Design

Fig. 1 shows the architecture of our latest system design. Stage 1 is the stage of raw data collection. From top to center, we have the process of collecting real radar signals with Synthetic Aperture Radar (SAR) operations using a mmWave FMCW radar sensor IWR6843ISK [1] and a data capture card DCA1000EVM [2] from Texas Instrument, configured by the mmWave studio [3]. A depth camera ZED mini [4] captures 2D depth images from the scenes. From bottom to center, we convert CAD models in point-cloud format using FreeCAD [5][6], then synthesize the radar signals and 2D depth images in MATLAB. The radar data will be processed in MATLAB [7] to generate the 3D intensity maps. Specifically, full-scale 3D intensity maps are generated from radar data with a 64x24 virtual antenna arrays, while the 2-snapshot 3D intensity maps are generated from the two center rows (2x24) of corresponding full-scale virtual antenna array.

In stage 2, the system includes Neural Networks written in Python taking the 2-snapshot 3D intensity maps as inputs, full-scale 3D intensity maps and the depth images as ground truths for reference, to train AI models for producing full-scale intensity maps from 2-snapshot intensity maps [8], and producing 2D depth images from either type of intensity maps. In stage 3, we have an UAV platform carrying a customized 2D sliding mechanism and mmWave radar sensor to collect 2 snapshots of SAR data of a scene. Then using the trained AI models, the system is able to generate full-scale 3D intensity maps or 2D depth images of this scene.

As shown in Fig. 2, our UAV platform is controlled by an open-source flying development platform called Crazyflie [9], with a BigQuad deck [10] extending the features to a bigger drone frame. The Crazyflie, BigQuad deck, and a flow deck [11] are located at the bottom, and a multi-ranger deck [12] at the top of the UAV. The flow deck is used to measure the distance to the ground for the drone to hover, while the multi-ranger deck is used for sensing the surrounding and ceiling while flying indoor. To connect the two sensor decks for Crazyflie, we designed a pair of PCB deck connectors with FFC connections, as shown in Fig. 3. The UAV is also equipped with a 3D-object reconstruction system, including a computing unit Jetson Nano [13] in the middle layer, a depth camera ZED mini on the top, and a mmWave radar sensor IWR6843ISK on a customized 2D-sliding mechanism in the front. The 2D-sliding mechanism is controlled by the Jetson Nano through stepper motors, timing belts and gear set from the back of the UAV.

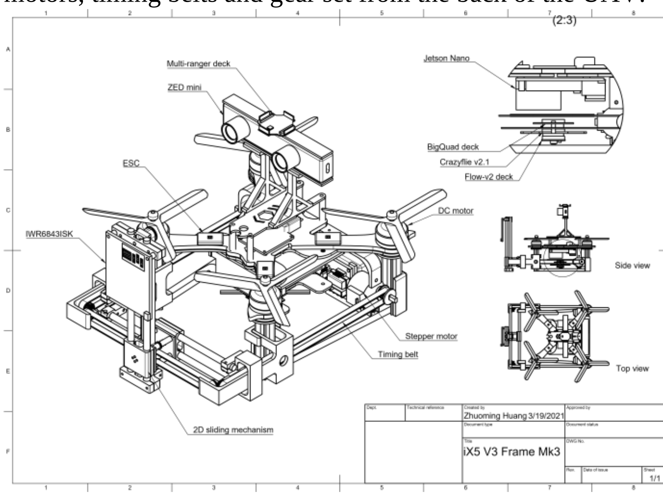

Fig. 2. UAV Platform Design.

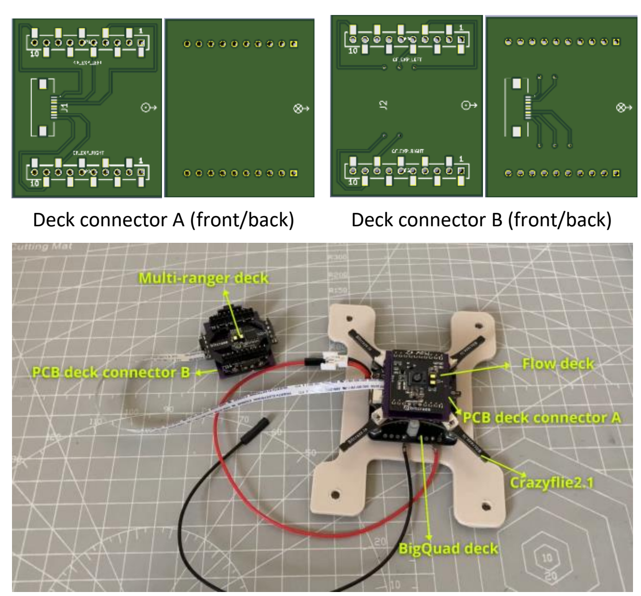

Fig. 3. PCB Deck Connectors.

IV. SYSTEM IMPROVEMENTS

A. Larger size of antenna array

When forming a Synthetic Aperture Radar (SAR), instead of using 64 vertical positions with 8 virtual antennas in horizontal direction, we move the radar sensor horizontally to add 2 more horizontal groups to create a 64x24 antenna array to improve the azimuth angular resolution increases from 15° to 5°.

B. Synthesizing data for model training

For training a neural network model, we plan to use at least 2500 data samples. However, it takes at least 1 hour to create a 64x24 SAR to collect one data sample in real experiments. Using synthesized radar data from CAD models, we are able to generate one data sample in about 1 minute, which speeds up the process of data sample collection.

C. Unifying coordinate system for model training

The coordinate system of the radar intensity maps is originally spherical. We converted it to Cartesian coordinate system so that it matches the coordinate system of the depth camera.

D. Stable and adjustable 2D-sliding mechanism

Utilizing T-slotted rails to hold the ball-screw slides that allows 5 to 10 cm adjustment in vertical direction.

E. Drone design

Based on the first drone design that was controlled by the Crazyflie2.1 with BigQuad and Flow-v2 decks, we added a Jetson Nano, a StereoPi camera, and a stronger base in the second design. In the latest design, we added a 3D-printed 2D-sliding mechanism, TI's IWR6843ISK mmWave radar sensor, and a Multi-ranger deck. We also replaced the StereoPi with a ZED mini depth camera.

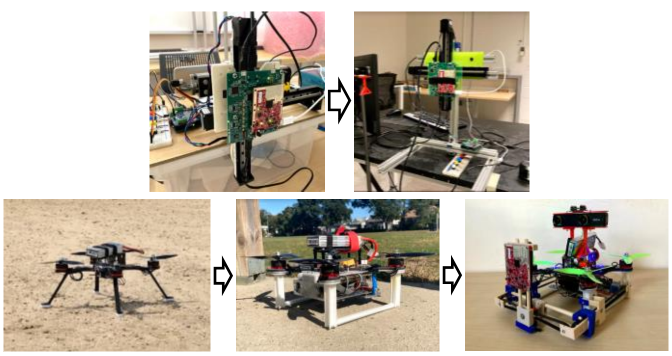

Fig. 4. Design Improvements.

V. TEAM ROLES

Basic members of the project are Zhuoming Huang and a junior observer Alinson Sanquintin. Zhuoming collects and synthesizes radar and camera sensor data for model training, processes collected data in MATLAB, tests and analyzes the subsystems, integrates all subsystems with an open-source UAV platform, and communications with our customer mentor as well as technical manager (CM/TM) Dr. Zhang. Alinson helps creating CAD models and converting them into point-cloud format for synthesizing data, and assists Zhuoming to do verification tests.

For any requirement on deep learning and model training, we have Yue Sun who is a PhD student helps to build deep neural networks to train AI models to generate 3D radar intensity maps or 2D depth images. We also have Lucas E. Lomba to provide us advices for PCB design and UAV design.

VI. COMMUNICATION PLAN

We have weekly meetings on Monday or Wednesday from 3:30PM to 5:30PM on Zoom, and in-person meetings in room M-3-316 on campus from 12:00PM to 3:00PM on Friday. We also have files sharing on Google drive, GitHub, and Dropbox.

VII. PROJECT MANAGEMENT

Basically, we have four milestones for this project. In September 2020, we did research on how to configure the mmWave radar sensor and depth camera, and determine the formal design. From October to December 2020, we collected the first few sets of data, tried to train our own Deep Neural Network models. During the winter break, we had found a way to convert CAD models into point-cloud format in FreeCAD [6], and tried to catch up with the schedule. From February to March 2021, we improved our hardware designs including the customized 3d-printed 2d-sliding mechanism, PCB deck connectors for flight control module of the drone, a new framework for raw data collecting process. We also performed a series of tests to verify our subsystems and system. From April to May, we performed some additional tests, especially the flight tests. We had finished the program for autonomous raw data collecting. And we decided to redesign the drone. Details of project management are shown in Fig. 5.

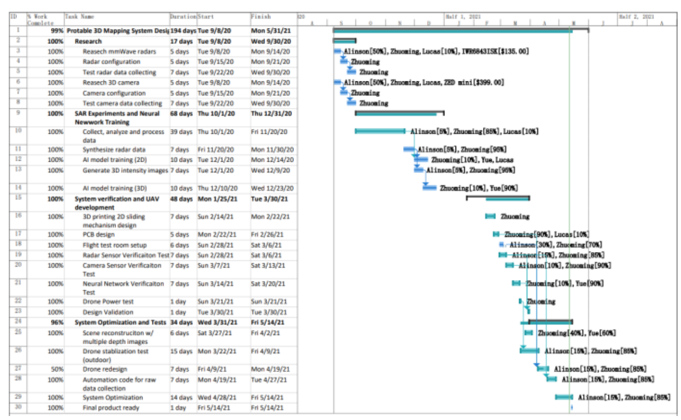

Fig. 5. Gannt Chart in Microsoft Project.

VIII. DESIGN VALIDATION AND DATA

To validate our design, we conducted four verification tests for our subsystems.

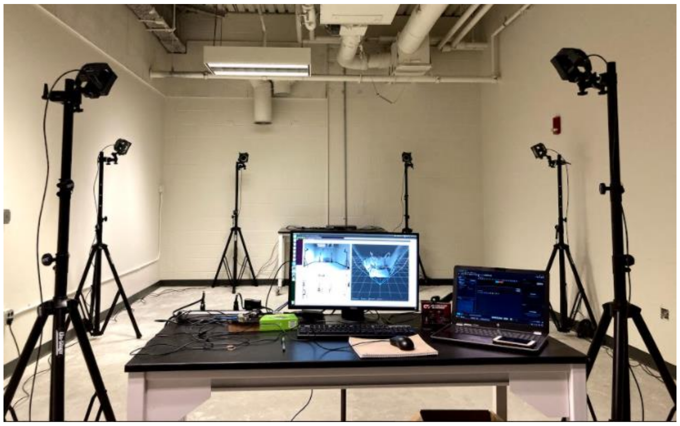

Fig. 6. Test environment for tests of depth camera and mmWave radar sensor.

A. Depth Camera Test

First of all, we have conducted a test to verify the accuracy of the depth camera ZED mini. For reference, we used the measurements by OptiTrack system [14] as ground truth. In a room with nonuniform light, we placed markers on the corners, edges, and surfaces of objects such as boxes and desks. We captured the 2D depth images of the scenes with the depth camera, and record the positions of markers with the OptiTrack system. Both devices recorded the depth or positions of markers via videos, then, we extracted or calculated the distance from the depth camera to each of the markers over 100 frames of the videos.

For the results of the test, we classified them into four categories based on the combinations of brightness (high/low) and contrast (high/low). We determined the brightness of an object by taking a look at the brightness images to see if it is higher or lower than the 50% of the highest brightness in the room. And we determined the contrast by seeing whether an object can be distinguished from the background or its surrounding. Fig. 7 shows the examples of four visibility conditions. Regardless of brightness, in the situations of high contrast, the corners and edges of the objects can be seen clearly in depth images, but in the situations of low contrast, the corner, edge, and even the surface are blurred or mixed with the background.

The plots in Figures 8-12 show the error in distance measurements under four different visibility conditions. From results shown in Fig 7, we can tell that the measurements are more accurate with higher brightness under same contrast, or higher contrast under same brightness. From results in Figures 8-11, we can tell that the measurements are more stable for the cases of higher contrast.

As a result shown in Table I, the %Error in distance measurements with the ZED mini depth camera is less than 1.8% with high brightness and high contrast, is less than 5.6% with high brightness and low contrast. For the cases of low brightness on the object, the %Error is less than 11.5% and 21% for high contrast and low contrast, respectively.

As listed in the datasheet, ZED mini has a depth accuracy of less than 1.5% up to 3m, and less than 7% up to 15m. Compare with the manufacture specification [15], or requirement of our design, the ZED mini we tested passed the test under high brightness and high contrast conditions.

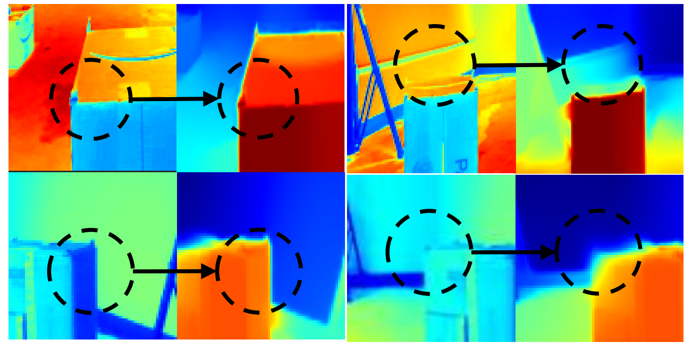

Fig. 7. Examples of pairs of brightness and depth images under four different visibility conditions: (a) high brightness with high contrast, (b) high brightness with low contrast, (c) low brightness with high contrast, (d) low brightness with low contrast.

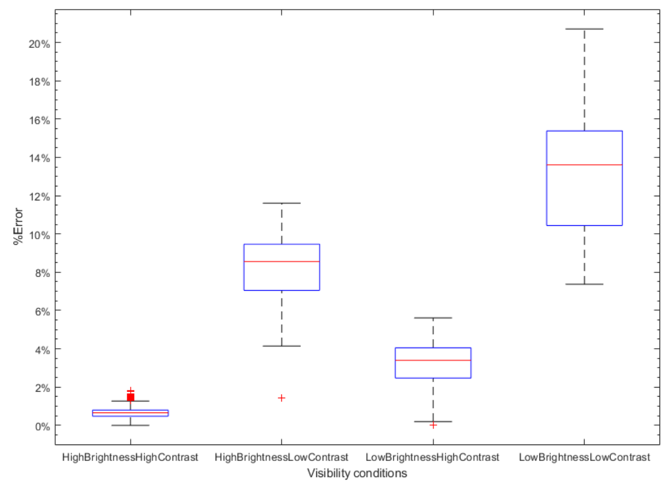

Fig. 8. Overall %Error of ZED mini in distance measurements under the four visibility conditions.

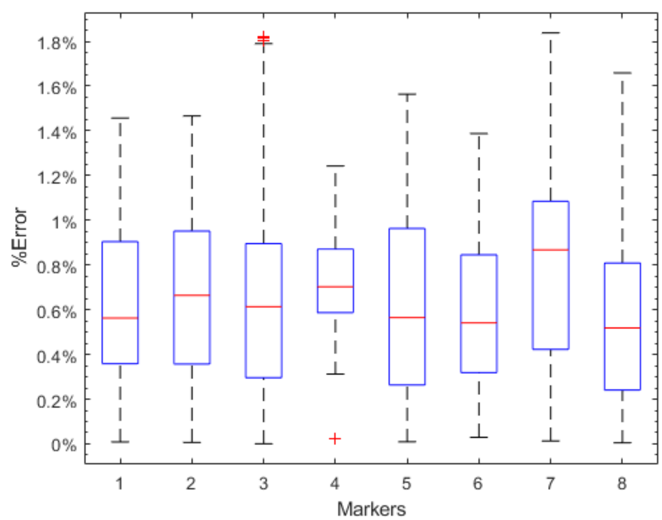

Fig. 9. %Error of ZED mini in distance measurements to 8 markers under high brightness and high contrast.

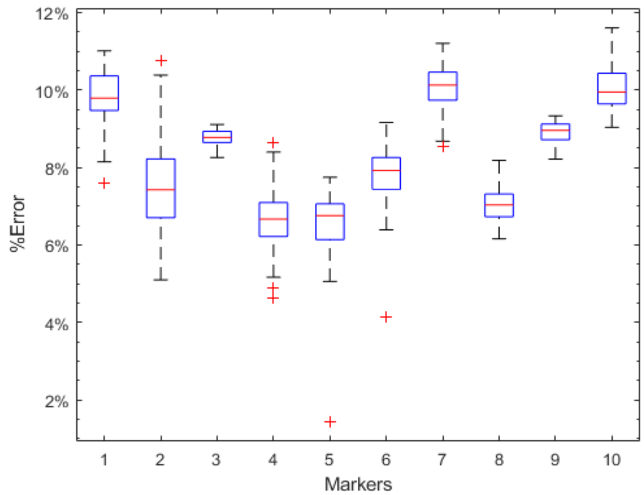

Fig. 10. %Error of ZED mini in distance measurements to 10 markers under high brightness and low contrast.

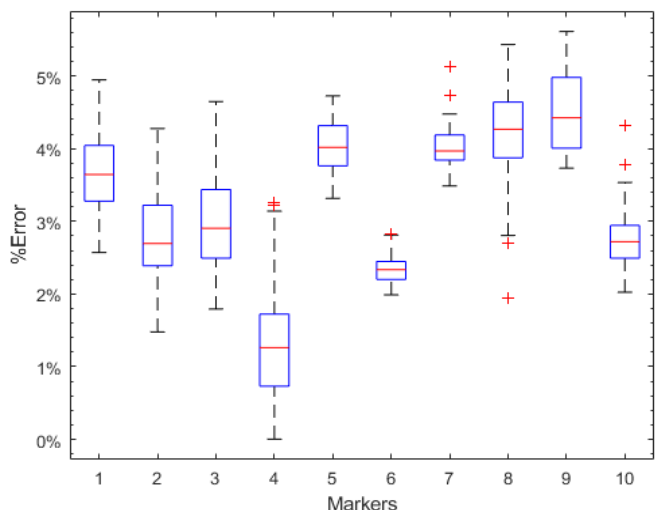

Fig. 11. %Error of ZED mini in distance measurements to 10 markers under low brightness and high contrast.

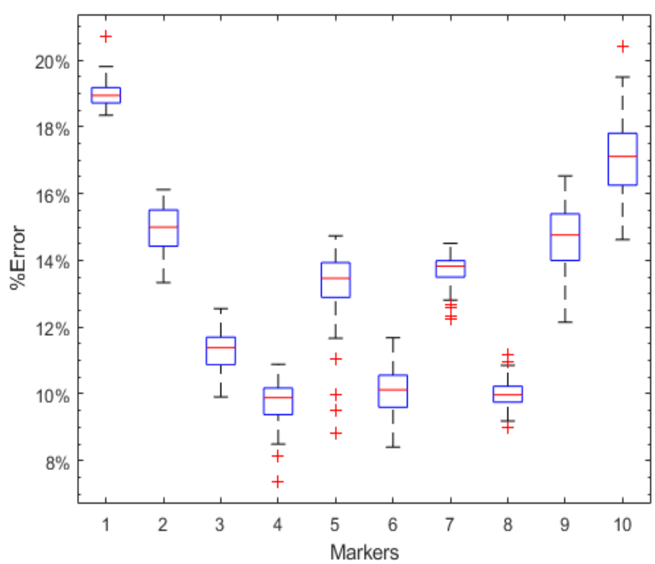

Fig. 12. %Error of ZED mini in distance measurements to 10 markers under low brightness and low contrast.

TABLE I
ACCURACY OF ZED MINI IN DISTANCE MEASUREMENTS

	High Contrast	Low Contrast
High Brightness	<1.8%	<11.5%
Low Brightness	<5.6%	<21.0%

B. *mmWave Sensor Test*

Similarly, we used the OptiTrack system for reference to test our mmWave radar sensor IWR6843ISK. We placed the objects at some distance to the radar sensor. For each object, we placed the markers at the four corners of the surface facing towards the radar sensor. Then we measured and compare the distance from the radar sensor to that surface over 100 frames or chirps of signal.

We chose three different materials for the test, including a metal plate that reflects strong radar signal, a paper box that allows radar signal to penetrate and reflects weak radar signal, and a foam board with thickness that creates multiple paths of reflections. For each material, we measured the distance to the object at 3 meters and 5 meters away. However, because of the size of the room, we were not able to give a test to radar's maximum range of 10 meters.

From the results shown in Fig. 13 and 14, we see that the error in distance measurement can be as small as 0.34% with strong signal reflection, and up to 1.95% with weak and scattered signal reflection.

For the angle measurements, we have the error up to 16.5% in azimuth and 4.3% in elevation. These larger errors in angle measurements are reasonable because of the low angular resolution, especially in azimuth direction. The angular resolutions are related to the size of antenna array. Larger size of antenna array allows higher angular resolution but it needs significantly more time to collect data. Our design with a 64x24 antenna array gives us an elevation resolution of 1.8° and an azimuth resolution of 4.8°, but it takes us about 1 hour for collecting one set of raw radar data.

The mmWave radar sensor IWR6843ISK passed the test in distance measurement, but failed in angle measurements. Because of the sparse radar signal and the low angular resolution, it is difficult to obtain the accurate measurement in angles of objects and their boundaries. This result points out that we do need the depth camera to obtain the shape of objects instead of using the radar sensor only.

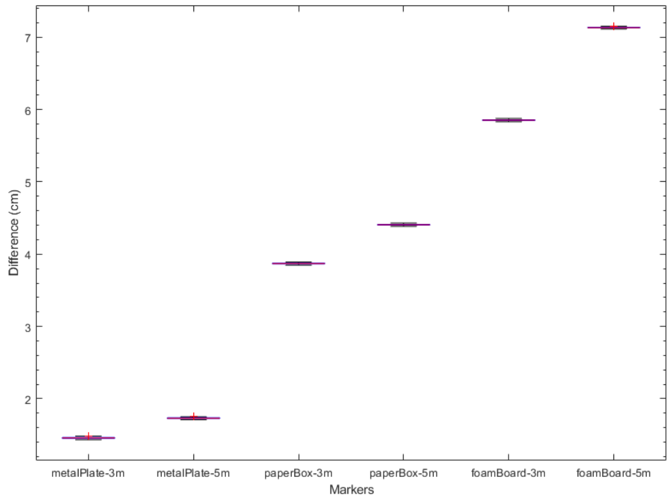

Fig. 13. Difference in measurements of distances to a metal plate, a paper box, and a foam board at 3m and 5m away. Results are measured by IWR6843ISK in compare to the OptiTrack.

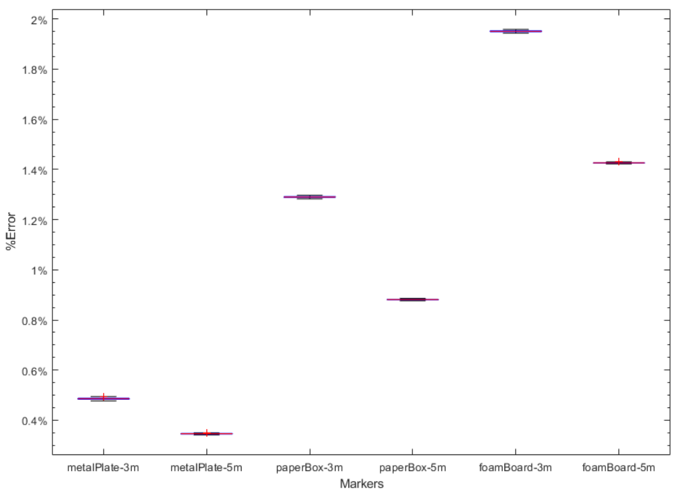

Fig. 14. %Error in measurements of distances to a metal plate, a paper box, and a foam board at 3m and 5m away. Results are measured by IWR6843ISK in compare to the OptiTrack.

TABLE II
RESULTS OF IWR6843ISK IN DISTANCE MEASUREMENTS

	Metal Plate		Paper Box		Foam Board	
	Diff	Err	Diff	Err	Diff	Err
3m	1.43cm	0.48%	3.85cm	1.29%	5.87cm	1.95%
5m	1.73cm	0.34%	4.43cm	0.88%	7.15cm	1.42%

TABLE III
ACCURACY OF IWR6843ISK IN ANGLE MEASUREMENTS

Azimuth	Elevation
<16.5%	<4.3%

C. *Neural Network Test*

For our Neural Networks, we specifically tested the workflow from 2-snapshot 3D radar intensity maps to 2D depth images. We used 2475 synthetic data samples (pairs of 3D radar intensity maps and 2D depth images to train an AI model, and verify it with 25 data samples.

For the results, we classified them into three categories: good, acceptable, and bad. A good result means that the object in the AI-generated depth image matches the color, size, shape, and orientation of the object in the true depth image. Acceptable means that the objects are matched in color but not perfect in size and orientation. And bad means they have completely different sizes and/or orientations. We have 14 results can be considered as good, 6 as acceptable, and 5 as bad. In other words, 56% of the results are good, or 80% are not bad.

We also performed another test on the L-shaped boxes with 400 real data and 2400 synthetic data, where 2500 are used for training and 300 are used for verification. The results are worse than the previous one, with only 42% are good and 77% are not bad, due to the complexity of real experiment environment, and the dependence of depth camera on visibility conditions. The losses of generator and discriminator are shown in Table IV.

TABLE IV
LOSSES OF OUR NEURAL NETWORK

	Full Synthetic	Half Real Half Synthetic
Generator Losses		
G_GAN	0.693	0.693
G_L1 (*1000)	2.861	26.244
G_Lp (*20)	21.452	21.651
Discriminator Losses		
D_real	0.693	0.408
D_fake	2.861	0.694

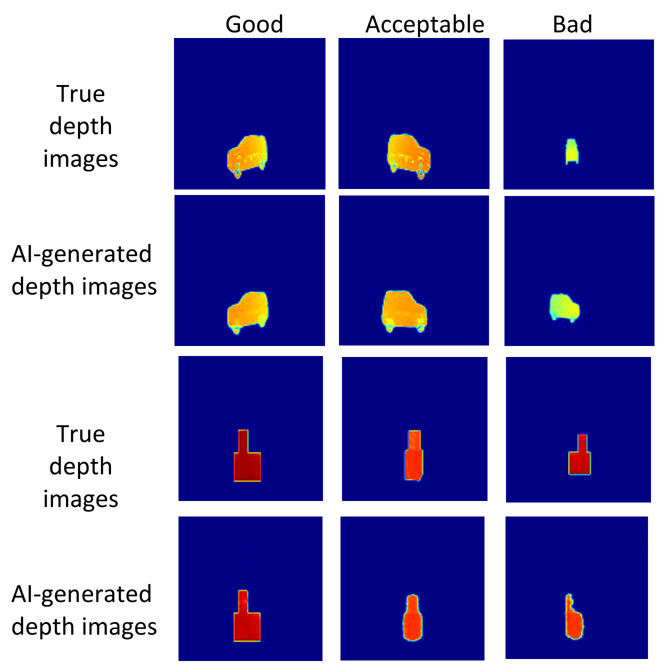

Fig. 15. Examples of results from NN test. The top two rows of images are based on synthesized radar data only. The bottom two rows of images are based on a mixture of synthesized and real radar data.

D. *Power Supply for UAV*

We tested the battery we used for the UAV by running the motors at different settings of throttle, and recording the voltage of battery every 5 minutes. Since the drone is still being developed, we were not able to test it with all devices, and that's what we need to do in the future. The battery we are using has a rated voltage of 11.1V. As the results in Table V suggested, considering the power consumption of other devices, we should keep the flight no more than 10 minutes, and pay attention to the battery status when it is close to 10 minutes. In practice, we need about 5 minutes to collect 2 snapshots of raw radar data on our UAV platform. In this case, the battery passed the test. However, if we want to collect multiple sets of data in one flight, the battery will fail the test. Therefore, we are considering a higher capacity battery to support a long flight time. And we want to have a larger drone frame and more powerful motors to reduce the workload of motors themselves and the battery when flying since less throttle will be needed to carry the same weight.

TABLE V
BATTERY TEST RESULT

	Battery Voltage (V)		
Time (min)	50% Throttle	75% Throttle	100% Throttle
0	12.53	12.51	12.60
5	12.46	12.40	11.73
10	12.35	11.99	11.34
15	11.72	11.16	11.13
20	11.15	10.95	9.65

IX. DELIVERABLES

The expected deliverable will be a 3D-object reconstruction system which can generate depth images from the sparse and raw mmWave radar data, including a 2D-sliding mechanism for collecting raw data, MATLAB programs for generating 3D radar intensity images and 2D depth images, and neural networks for training AI models, an UAV platform with an SAR mechanism holding and moving the radar sensor and depth camera, as shown in Fig. 16.

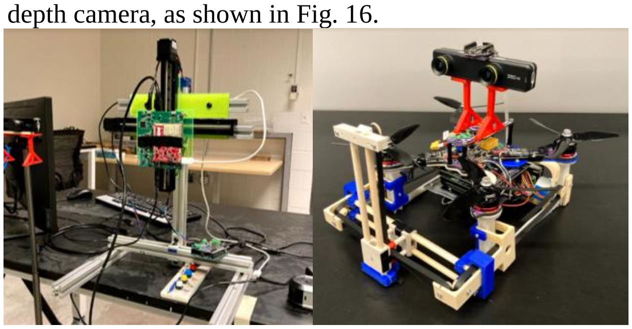

Fig. 16. Deliverables (a) data-collecting equipment for model training (b) UAV platform with customized 2D-sliding mechanism.

X. COMPONENTS AND BUDGET

Table VI and VII show the necessary components for building our design, and the components we have purchased.

In our design, we have two sets of hardware equipment, including a one-time-used raw data collecting equipment for model training, and an UAV platform. IWR6843ISK and ZED mini are common in both hardware equipment. DCA1000EVM, ball-screw slides, Arduino Uno, Adafruit motor shield, and the T-slotted frame are used for model training part only. The rest of the components in Table VI are used on the UAV platform.

In this project, we have the raw-data-collecting equipment to collect the raw radar data and train our own models for purpose of verifications. To build a UAV mmWave SAR/Depth Camera system with pre-trained deep neural network models, the total budget is only about $980.

TABLE VI
REQUIRED COMPONENTS

Item	Qty	Price	Note
IWR6843ISK	1	$135	mmWave radar sensor
ZED mini	1	$399	3D depth camera
DCA1000EVM	1	$499	Data capture card
Ball-screw slide	2	$140	Moves sensor to form SAR
Arduino Uno	1	$23	Slide controller
Adafruit motor shield	1	$20	Slide motor driver
T-slotted frame	1	$40	Holds ball screw slides
Oshpark PCBs	1	$21	Deck connectors
WE FFC connector	10	$13	For PCBS
Jetson Nano	1	$99	Computing unit on UAV
Crazyflie set	1	$327	Flight control, including Crazyflie2.1, BigQuad, Flow-v2, multi-ranger decks
Customized 2D sliding mechanism	1	$10	Forms an SAR on UAV
Total		$1731	Model training + UAV sensing equipment
Final budget		$980	UAV sensing equipment

TABLE VII
PURCHASED COMPONENTS AND USED BUDGET

Item	Qty	Price	Note
IWR6843ISK	1	$135	mmWave radar sensor
ZED mini	1	$399	3D depth camera
Ball-screw slide	4	$280	Moves sensor to form SAR
Arduino Uno	1	$23	Slide controller
Adafruit motor shield	1	$20	Slide motor driver
T-slotted frame	1	$40	Holds ball screw slides
Oshpark PCBs	1	$21	Deck connectors
WE FFC connector	10	$13	For PCBS
Jetson Nano cooling fan	1	$14	
Customized 2D sliding mechanism	1	$25	Forms an SAR on UAV
5V,2.5A power cable	1	$10	
Used budget		$980	

XI. ETHICAL CONSIDERATION

When conducting outdoor experiments, operators should ask for a permission if any private property is involved. In public areas, we should keep the camera off if it is not necessary to use it or someone doesn't feel comfortable in front of it. For the flight tests, operators should always wear safety glasses and cut-resistant gloves, and check status of battery, motors, and propellers before the launch. Operators must follow the covid-19 guidelines to wear masks and keep a social distance.

XII. Conclusion and Future work

We have designed a system for fast 3D-object reconstruction in low-visibility environment through mmWave radar sensing, with Neural Networks for enhancing the intensity maps generated from sparse radar data to a higher resolution, and producing 2D depth images with accuracy comparable to depth cameras. As we evaluated our design, the mmWave radar signal is too sparse to obtain accurate shape information of objects, depth camera is not stable when measuring depth in low-visibility environments. However, the depth camera we used has an error less than 1.8% in depth sensing under high brightness and high contrast conditions. Currently, we are able to reconstruct one surface of an object that is visible by the sensors from a 2D depth image. In future work, we will seek a quantitative way for evaluating our Neural Networks, redesign the UAV platform with bigger drone frame, more powerful motors and propellers, higher capacity battery, and better PID tuning to have a larger load and longer flight time. We will also improve the resolution of AI-generated depth images and build Neural Networks with inputs in multiple views to achieve more features for reconstructing objects especially for small objects, and for reconstructing the complete surface of objects from data in multiple views.

Appendix

A. Hawkeye Radar Synthesizer

- Inputs:

1) CAD model 3D physical point cloud
2) Scene parameters (scene boundary, translation/rotation resolutions)
3) Radar parameters (FOV in range/azimuth/elevation, sample#, sample rate, center/starting frequency, sweep slope, bandwidth, wavelength, number of bins, antenna#, antenna spacing)

- Procedure:

4) Translate and rotate the CAD model point cloud within the scene boundary
5) Select the points as radar signal reflectors from the CAD model point cloud
6) Simulate received radar signal in receiver antenna array based on radar configuration
7) Generate the 3D radar intensity heatmap from the radar reflector point cloud

- Outputs:

1) Radar 3D intensity heatmap (spherical coordinates)
2) Optional:
   a. translated CAD model point cloud (over 100MB)
   b. radar reflector point cloud
   c. simulated radar signal in receiver antenna array

B. Depth Image Generation from Point Cloud

- Input:

1) CAD model 3D physical point cloud
2) Camera FOVs, resolution, focal length, scene size

- Procedure:

1) Select the points as camera reflectors from the CAD model point cloud

2) Further filter out the sparse points at the back but not being blocked (optional)
3) Calculate the distance of each point to the camera (depth)
4) Calculate the coordinates of each point onto the image plane after perspective projection
5) Construct a mesh grid centered at the image plane, grid size matches the pixel size
6) For the grids(cells) that cover multiple points, leave the point with minimum depth

- Output:

1) 2D depth image (Perspective projection)

C. FreeCAD Point Cloud Conversion

1) Import or create a CAD model in FreeCAD
2) Select workbenches 'Mesh Design' in tab 'View'
3) Select create mesh from a shape in tab 'meshes'
4) Select workbenches 'Points'
5) Select convert to points in tab 'points'

D. List of files

1) MATLAB
- Hawkeye synthesizer
- Depth image generator
- 3D intensity convertor
- 3D point cloud reconstruction

2) Python
- ZED mini SDK, depth image processing
- Matrix file to pickle file convertor

3) Documentation
- DCA1000EVM manual
- mmWave Studio manual
- Technical report

E. Components

1) TI IWR6843ISK mmWave radar sensor with DCA1000EVM data capture card
- Number of virtual antennas: 24 in azimuth, 64 in elevation
- Angular resolution: approx. 4.8 degrees in azimuth, 1.8 degrees in elevation
- Start frequency: 60GHz
- Frequency slope (sweep slope): 29.982 MHz/us
- Idle time: 100 us
- ADC start time: 6 us
- Number of samples: 256
- Sample rate: 2047 ksps
- Ramp end time: 133 us

- RX gain: 30 dB
- Bandwidth: 3987.61 MHz

2) ZED mini depth camera

- Resolution: HD720
- Width: 1280
- Height: 720
- Focal length: 700 pixels, or 2.8 mm
- Pixel size: 0.004 mm
- V FOV: 54 degrees
- H FOV: 85 degrees
- fov = 2*arctan(pixelNumber/(2*focalLength))*(180/pi)

ACKNOWLEDGMENT

This project is supervised by Dr. Honggang Zhang, who is our customer mentor and technical manager. Except the components we ordered with senior design funds, all other equipment and components are provided by Dr. Zhang 's Pervasive Computing Lab in the Engineering Department. We especially would like to than Yue Sun, a PhD student advised by Dr. Zhang, for building Deep Neural Networks. We would like to thank Dr. Tomas Materdey for teaching the senior design courses, and Dr. Michael Rahaim for providing us the OptiTrack system, and Andrew Davis for helping us with various resources. We also thank Lucas Lomba of Pervasive Computing Lab for helping us with drone design.

REFERENCES

[1] Texas-Instruments, *IWR6843ISK*, 2021 [Online]. Available: https://www.ti.com/tool/IWR6843ISK

[2] Texas-Instruments, *DCA1000EVM*, 2021 [Online]. Available: https://www.ti.com/tool/DCA1000EVM

[3] Texas-Instruments, *mmWave Studio*, 2021 [Online]. Available: https://www.ti.com/tool/MMWAVE-STUDIO

[4] STEREOLABS, *ZED mini*, *2021* [Online]. Available: https://www.stereolabs.com/zed-mini/

[5] J. Guan, S. Madani, S. Jog, and H Hassanieh. " High Resolution Millimeter Wave Imaging for Self-Driving Cars.". 2020. *IEEE CVPR (2020).*

[6] FreeCAD, *FreeCAD*, 2020 [Online]. Available: https://www.freecadweb.org/

[7] MathWorks, *MATLAB*, 2021 [Online]. Available: https://www.mathworks.com/products/matlab.html

[8] S. Fang and S. Nirjon. "SuperRF: Enhanced 3D RF Representation Using Stationary Low-Cost mmWave Radar." 2020. *International Conference on Embedded Wireless Systems and Networks (EWSN),* Vol. 2020. NIH Public Access, 120.

[9] Bitcraze, *Crazyflie*, 2020, [Online]. Available: https://www.bitcraze.io/crazyflie-2/

[10] Bitcraze, *BigQuad deck*, 2020, [Online]. Available: https://www.bitcraze.io/products/bigquad-deck/

[11] Bitcraze, *Flow deck*, 2020, [Online]. Available: https://www.bitcraze.io/products/flow-deck-v2/

[12] Bitcraze, *Multi-ranger deck*, 2021, [Online]. Available: https://www.bitcraze.io/products/multi-ranger-deck/

[13] NVIDIA, *Jetson Nano Developer Kit*, 2020, [Online]. Available: https://developer.nvidia.com/embedded/jetson-nano-developer-kit

[14] LEYARD, *OptiTrack*, 2021 [Online]. Available: https://optitrack.com/

[15] STEREOLABS, "ZED mini Datasheet_2019_rev1," 2021, [Online]. Available: https://cdn.stereolabs.com/assets/datasheets/zed-mini-camera-datasheet.pdf