Diagnosing Electrical Appliance Health for Predictive Maintenance using mmWave Radar

A Thesis Submitted for the Degree of Master of Computer Science

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Declaration

Name of the student: P.A.P.P. Gunarathne
Registration number: 2019/MCS/033
Name of the Degree Programme: Master of Computer Science
Project/Thesis title: Diagnosing Electrical Appliance Health for Predictive Maintenance using mmWave Radar

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	Supervisor 1	Supervisor 2	Supervisor 3
Name	Dr. Asanka P. Sayakkara		
Signature			
Date	2024-10-26		

I would like to dedicate this thesis to my parents, my teachers, my friends and all, whose unwavering love, support, and encouragement have been the guiding lights throughout my academic journey

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I would like to express my deepest gratitude to all those who have contributed to the completion of this research project on "Diagnosing Electrical Appliance Health for Predictive Maintenance using mmWave Radar." Without their support, guidance, and encouragement, this endeavor would not have been possible.

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In conclusion, I am profoundly grateful to all those who have contributed to this research project in various capacities. Their collective efforts and support have played a pivotal role in shaping the outcome of this study and have enriched my academic and personal growth.

Thank you in advance.

ABSTRACT

Electrical appliances are ubiquitous in modern households and industries, playing a crucial role in daily operations. However, the reliability and longevity of these appliances can be compromised by wear and tear, electrical faults, or other issues that may arise over time. To address this challenge, we propose a novel approach for diagnosing the health of electrical appliances using millimeter-wave (mmWave) radar technology. In this research, we leverage the unique capabilities of mmWave radar sensors to remotely monitor the condition of electrical appliances without the need for physical contact. By analyzing the reflections of mmWave signals from the surfaces of appliances, we can extract valuable information about their structural integrity, operational status, and potential faults. Key aspects of our approach include extracting data from mmWave sensor and processing them for appliance health diagnosis, which enable the detection of anomalies such as loose connections, insulation degradation, and mechanical wear. Furthermore, we explore the use of machine learning techniques to enhance the accuracy and reliability of appliance health assessment based on radar data. Through experimental validation and real-world deployment scenarios, we demonstrate the effectiveness and feasibility of our proposed method for predictive maintenance of electrical appliances. As per the analysis done throughout this research when a healthy electrical device is near the sensor, the Doppler index values, which represent frequency values are shifted to the right and when a faulty device is near by the values are more shifted to the left. By proactively identifying impending issues and scheduling maintenance tasks accordingly, our approach can help prevent costly downtime, improve energy efficiency, and prolong the lifespan of electrical appliances. Overall, this research contributes to advancing the field of predictive maintenance by harnessing the capabilities of mmWave radar technology for non-invasive, remote diagnosis of electrical appliance health, with potential applications in both residential and industrial settings.

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CHAPTER 1 INTRODUCTION

Electrical appliances are essential components of modern life, serving critical functions in both residential and industrial settings. From refrigerators and air conditioners to manufacturing machinery and power distribution systems, these appliances play a pivotal role in our daily lives and business operations. However, like any mechanical or electrical system, they are prone to degradation, wear, and potential failure over time. Unplanned downtime due to appliance failures can result in significant inconvenience, loss of productivity, and costly repairs.

To mitigate these risks and ensure the reliable operation of electrical appliances, proactive maintenance strategies are essential. Traditional approaches to maintenance often rely on scheduled inspections or reactive repairs, which may not effectively address underlying issues or prevent unexpected failures. Moreover, manual inspection methods can be labor-intensive, time-consuming, and prone to human error.

In this context, there is a growing need for innovative techniques that enable the early detection of appliance health issues and facilitate predictive maintenance practices. One promising technology that has garnered increasing attention for its potential in this domain is millimeter-wave (mmWave) radar. MmWave radar sensors offer unique capabilities for non-contact, remote sensing of objects and surfaces, making them well-suited for monitoring the condition of electrical appliances without the need for physical access.

The objective of this research is to explore the feasibility and efficacy of using mmWave radar technology for diagnosing the health of electrical appliances and enabling predictive maintenance strategies. By leveraging the principles of radar sensing and signal processing, we aim to develop a novel approach that can accurately detect anomalies, faults, and degradation in appliance components. This proactive approach to maintenance can help minimize downtime, optimize resource utilization, and extend the lifespan of electrical appliances.

In this introduction, we will provide an overview of the challenges associated with traditional maintenance practices, highlight the potential benefits of adopting predictive maintenance strategies, and outline the objectives and scope of our research. We will also discuss the significance of leveraging mmWave radar technology for appliance health diagnosis and present an outline of the subsequent chapters of this study.

1.1 Motivation

Conducting a study on diagnosing electrical appliance health using mmWave radar is motivated by the need to enhance maintenance practices, mitigate downtime risks, and optimize the performance and lifespan of electrical appliances in diverse applications.

1.2 Statement of the problem

How can mmWave sensing technology be effectively utilized for detecting the health conditions of electrical appliances?

With the increasing complexity and miniaturization of electrical appliances, ensuring their health and performance is a critical concern. Traditional diagnostic methods often involve physical inspections or manual testing, which can be time-consuming and intrusive. In recent years, millimeter-wave (mmWave) sensing technology has emerged as a promising solution for non-contact, non-intrusive monitoring and assessment of electrical appliances' health conditions. In general, sometimes it would be difficult to contact technicians due to their availability to check the health condition of the electrical appliances. By accurately detecting and localizing these issues, early intervention, repair, or replacement can be initiated, ensuring the longevity, real time monitoring and optimal functioning of the electrical appliances, i.e., predictive maintenance.

At the end of this research, the following questions will be answered:

1. How can mmWave sensing technology be effectively utilized for detecting the health conditions of electrical appliances?
2. What are the key parameters and metrics that can be derived from mmWave sensing data to assess the health status of electrical appliances?

1.3 Research Aim and Objectives

The primary focus of your research is usually expressed in terms of aims and objectives.

1.3.1 Aim

To develop a novel approach for diagnosing the health of electrical appliances using millimeter-wave (mmWave) radar technology.

1.3.2 Objectives

The primary objective of this research is to develop a Health Condition detecting system in electrical appliances that utilizes mmWave sensing technology for accurate and efficient identification of the health condition.

Investigate Feasibility:

Assess the feasibility of using mmWave radar sensors for non-contact, remote sensing of electrical appliance health. This involves evaluating the capabilities of mmWave radar in detecting anomalies, faults, and degradation in appliance components.

Validate Accuracy and Reliability:

Validate the accuracy and reliability of the proposed approach through empirical testing and experimentation. Compare the performance of mmWave radar-based diagnosis with traditional methods to assess its effectiveness in detecting and predicting appliance failures.

Explore Machine Learning Techniques:

Explore the use of machine learning techniques to enhance the accuracy and predictive capabilities of appliance health diagnosis based on mmWave radar data. Investigate the potential of machine learning models for pattern recognition, anomaly detection, and predictive maintenance.

Demonstrate Practical Applications:

Demonstrate the practical applications and benefits of mmWave radar-based appliance health diagnosis for predictive maintenance. This involves conducting real-world experiments in residential and industrial settings to showcase the utility and effectiveness of the proposed approach in diverse scenarios.

Provide Guidelines for Implementation:

Provide guidelines and recommendations for implementing mmWave radar-based appliance health diagnosis in practical maintenance workflows. Address considerations such as sensor placement, data acquisition, signal processing, and integration with existing maintenance systems.

Evaluate Cost-Effectiveness:

Evaluate the cost-effectiveness of adopting mmWave radar-based predictive maintenance strategies compared to traditional maintenance approaches. Consider factors such as equipment costs, maintenance savings, downtime reduction, and overall return on investment (ROI).

Contribute to Knowledge Base:

Contribute to the body of knowledge in the field of predictive maintenance by advancing understanding of the capabilities and limitations of mmWave radar technology for diagnosing electrical appliance health. Publish research findings in academic journals and present them at relevant conferences and seminars.

Finally, the ultimate goal of this research is to advance the field of detecting health conditions in electrical appliances by harnessing the capabilities of mmWave sensing technology. By developing an innovative and reliable system, this project will contribute to addressing the challenges associated with traditional Health Condition detecting methods, enabling more accurate mapping and monitoring of electrical appliances. The outcomes of this research have the potential to revolutionize diagnosing the health conditions of electrical appliances practices and support decision-making processes in various sectors, leading to improving the capabilities and benefits of using mmWave sensing technology and sustainable development.

1.4 Scope

One of the first tasks of a researcher is defining the scope of a study, i.e., its area (theme, field) and the amount of information to be included. Narrowing the scope of your thesis can be time-consuming. Paradoxically, the more you limit the scope, the more interesting it becomes. This is because a narrower scope lets you clarify the problem and study it at greater depth, whereas very broad research questions only allow a superficial treatment.

The scope of this study encompasses the development and evaluation of diagnosing the health conditions of electrical appliances utilizing millimeter wave (mmWave) sensing technology. The research will focus on the application of mmWave signals to accurately identify and characterize the faults of electrical appliances. Further this study involves understanding the principles, theory, and operation of mmWave sensing technology as it applies to diagnosing the health condition of electrical appliances. This includes reviewing relevant literature and understanding the current state of the technology.

The study will involve the following aspects:

Hardware Development:

The study will involve developing a hand-held device with a display unit which includes FMCW [1] radar device and some additional components such as IWR1843 BoostMaster mmWave sensor, DSA 1000 EVM (Evaluation Module) mmWave Demo visualizer tool and etc. Please note that this study includes the existing, off-the-shelf mmWave FMCW radar equipment.

Signal Processing Techniques:

The research will involve the development of signal processing techniques specifically tailored for mmWave-based diagnosing of electrical appliances. These techniques will be designed to analyze the received signals, extract relevant features, and differentiate faulty patterns from other patterns (active or normal). The techniques (Python language, data processing tools and etc) will aim to achieve high detection accuracy and minimize false positives or negatives.

Field Testing and Validation:

The study will include comprehensive field tests and validation experiments to assess the performance and reliability of the developed mmWave diagnosing system. These tests will involve collecting data from various real-world scenarios and comparing the results with actual data gathered from technical experts. The validation process will help evaluate the accuracy and effectiveness of the proposed technology.

Potential Applications:

The study will explore the potential applications and scalability of the mmWave health condition detection system. The research will consider factors such as cost-effectiveness, deployment flexibility, and integration with existing monitoring systems to assess the system's applicability in different contexts.

Limitations and Constraints:

The study will acknowledge and address the limitations and constraints associated with mmWave sensing technology for diagnosing health condition detection. These may include factors such as limited penetration depth, interference from environmental factors, and the need for accurate calibration and synchronization. The research will strive to identify these limitations and propose potential mitigation strategies.

It is important to note that this study will focus on the development and evaluation of diagnosing health condition detection systems for simple electrical devices such as Air conditioners, ceiling fans and etc, rather than the comprehensive mapping or monitoring of whole other resources on a global scale. The scope of the study will be defined within the resources, time constraints, and specific objectives outlined in the research proposal.

By investigating and developing the mmWave sensing technology for diagnosing the health conditions of electrical appliances, this study aims to contribute to the advancement of diagnosing management practices, support decision-making processes, and enable more accurate mapping and monitoring of electrical appliances. The outcomes of this study have the potential to benefit various sectors that rely on access to electrical appliances.

1.5 Structure of the Thesis

The organized structure of the thesis explained in the following paragraphs.

The Introduction chapter provides an overview of the research topic, outlines the research objectives, and presents the significance and motivation for the study. It may also include background information, a review of relevant literature, and an overview of the research methodology.

The Literature review chapter critically examines existing literature and research relevant to the topic of study. It identifies key concepts, theories, methodologies, and findings in the field, highlighting gaps, controversies, and areas for further investigation.

The Methodology chapter describes the research methods, techniques, and procedures employed in the study. It outlines the research design, data collection methods, data analysis techniques, and any tools or instruments used in the research process.

The Evaluation and Results chapter presents the research approach and the findings of the study, often through the presentation of empirical data, statistical analyses, tables, figures, and charts. It provides an objective summary of the research outcomes, organized according to research questions or hypotheses.

The Conclusion and Future work chapter summarizes the key findings of the study, reiterates the research objectives, and discusses the implications of the research findings. It may also reflect on the significance of the study, offer recommendations for practice or policy, and suggest directions for future research. Further this chapter interprets and contextualizes the results of the study, relating them to the research objectives and relevant literature. It examines the implications of the findings, identifies patterns or trends, discusses limitations, and proposes avenues for future research.

The references section lists all sources cited in the thesis, following a specific citation style (e.g., APA, MLA, Chicago). It provides readers with the information needed to locate and verify the sources referenced in the text.

The appendices section includes supplementary materials that support the main text of the thesis, such as additional data tables, survey instruments, interview transcripts, or software code.

CHAPTER 2 LITERATURE REVIEW

2.1 A Literature Review

The following papers present a comprehensive review of the related work and background study on the topic of Diagnosing the health condition in electrical appliances using mmWave sensing technology. It explores the principles, methodologies, and applications of mmWave sensing technology for health condition detection, highlighting the advantages and limitations of this approach. These papers also discuss the current challenges and future research directions in this field as well. Diagnosing the health condition in electrical appliances using mmWave sensing technology plays a vital role in various fields such as engineering, education, agriculture, etc. In recent years, mmWave sensing technology has emerged as a promising tool for monitoring and diagnosing health conditions in electrical appliances.

Diagnosing the health condition in electrical appliances is crucial for ensuring their reliable operation and preventing unexpected failures [2]. Traditional diagnostic methods often involve invasive techniques or require disassembly of the devices, which can be time-consuming, costly, and disruptive to the operational workflow [3]. To overcome these limitations, mmWave sensing technology has emerged as a promising non-invasive approach for diagnosing the health condition of electrical appliances.

The work presented by Yin, H., et al. (2018) [3] addresses the issue of diagnosing cracks in electronic packages, a common concern that can lead to device failure and compromised performance. The authors propose a noninvasive approach for crack detection using mm-wave scanning. The study presents a novel mm-wave scanning technique that utilizes mmWave electromagnetic waves to probe the electronic packages and identify cracks without the need for physical contact or disassembly. The mmWave signals are emitted towards the package, and the reflections and scattering patterns are analyzed to detect the presence and location of cracks. The authors describe the experimental setup and methodology for mm-wave scanning, including the selection of appropriate frequencies and the design of the scanning system. They conduct experiments on different types of electronic packages and demonstrate the effectiveness of their approach in detecting cracks with high accuracy. The results of the study [4] highlight the potential of mmWave scanning as a noninvasive diagnostic tool for assessing the health condition of electronic packages. The proposed technique offers advantages such as real-time monitoring, rapid screening, and the ability to detect hidden cracks that may not be visible through visual inspection.

Overall, the research paper [4] provides valuable insights into the application of mmWave scanning for noninvasive crack diagnosis in electronic packages. It contributes to the field of electronics reliability and offers a promising approach for improving the quality and performance of electrical appliances.

mmWave sensing technology utilizes millimeter-wave electromagnetic waves, typically in the frequency range of 30 to 300 GHz, to gather information about the internal structure and characteristics of the devices. By analyzing the reflections, scattering, and transmission of mmWave signals, it becomes possible to detect anomalies, faults, or degradation in the devices without the need for physical contact or disassembly. This non-contact nature of mmWave sensing makes it ideal for real-time monitoring, rapid screening, and continuous assessment of the health condition of electrical appliances.

In the context of diagnosing the health condition in electrical appliances, mmWave sensing can be applied to various areas, including Printed Circuit Board (PCB) assemblies, integrated circuits and electronic packages. It can help identify common issues such as cracks [4], delamination, voids, corrosion, fatigue, and aging effects that may impact the performance and reliability of the devices. By accurately detecting and localizing these issues, early intervention, repair, or replacement can be initiated, ensuring the longevity and optimal functioning of the electrical appliances.

The paper by Jin, Y., et al. (2022) [7] addresses the need for reliable and nondestructive methods to evaluate the health condition of integrated circuits. ICs are critical components in electrical appliances, and defects or anomalies in their structure can affect performance and reliability. Traditional evaluation methods often involve destructive testing or disassembly, which is not ideal for assessing ICs in operational devices. In this study [7], the authors propose a nondestructive approach based on mmWave reflective imaging for evaluating ICs. The mmWave signals are emitted towards the ICs, and the reflected signals are analyzed to obtain information about the internal structure and potential defects or anomalies. The paper describes the experimental setup and methodology for mmWave reflective imaging, including the selection of appropriate frequencies and imaging techniques. The authors conduct experiments on different types of ICs and demonstrate the effectiveness of their approach in identifying various types of defects, such as delamination, voids, and cracks.

The results of the study show that mmWave reflective imaging can provide valuable information about the internal structure and health condition of ICs without causing damage or disruption. The proposed nondestructive evaluation approach offers advantages such as real-time monitoring and rapid assessment. Further, the research paper contributes to the field of IC evaluation and demonstrates the potential of mmWave reflective imaging as a nondestructive technique. It provides insights into the application of mmWave technology for assessing the health condition of ICs and offers a promising approach for improving the reliability and performance of electrical appliances.

To leverage mmWave sensing for health diagnosis in electrical appliances, several research studies have been conducted. These studies focus on developing innovative sensing techniques, signal processing techniques, and diagnostic models specifically tailored for mmWave-based diagnostics. They explore the use of different mmWave sensors, such as radar systems or imaging devices, and investigate the feasibility, accuracy, and reliability of using mmWave sensing for health assessment.

The study [8] addresses the challenge of accurately measuring micrometer-level vibrations using mmWave radar. Existing methods were either intrusive or failed to capture such fine vibrations. In response, the researchers propose mmVib, a practical approach that leverages mmWave radar for precise vibration measurement [10].

Two key contributions stand out:

1. The Multi-Signal Consolidation (MSC) Model describes properties of reflected signals. By exploiting the inherent consistency among these signals, it accurately recovers vibration characteristics.

2. The Vibration Signal-to-Noise Ratio (VSNR) serves as a metric guiding effort to reduce measurement errors for tiny vibrations.

In experimental tests, the mmVib prototype achieved impressive accuracy:

- Relative Amplitude Error: 8.2% (median)
- Relative Frequency Error: 0.5% (median)

Compared to existing approaches, mmVib significantly reduces the 80th percentile amplitude error. Practical implications include applications in industrial systems for health monitoring, anomaly detection, and fault diagnosis. Moreover, mmVib offers moderate cost and low deployment expenses compared to other methods. The study contributes valuable insights to the field of wireless sensing and millimeter-wave technology.

The MSC model is a fundamental component of the mmVib approach. Here's how it works:

Signal Reflection Properties:

When a mmWave radar emits signals and they encounter a vibrating object (such as machinery or structures), they get reflected back. These reflected signals carry information about the object's vibration characteristics. The MSC model analyzes these reflected signals.

Consistency Among Reflected Signals:

The MSC model considers multiple reflected signals received from different angles. By examining the consistency among these signals, it extracts valuable information. Think of it as combining puzzle pieces from different angles to form a complete picture.

Signal Fusion and Vibration Recovery:

The MSC model fuses the information from various signals. It reconstructs the vibration characteristics (amplitude, frequency, etc.) of the object. This fusion process enhances accuracy, especially for micrometer-level vibrations.

Benefits of MSC model:

By leveraging the inherent consistency among signals, MSC achieves precise vibration measurement which expresses the accuracy of the MSC model. It handles noise and interference effectively which expresses the robustness of the MSC model. Unlike some traditional methods, MSC doesn't require physical contact with the vibrating object which expresses the non-Intrusive of the MSC model.

The MSC model enables mmVib to achieve remarkable accuracy in capturing tiny vibrations. It has practical implications in fields like industrial monitoring, structural health assessment, and fault detection. Further this model is a powerful tool for non-contact vibration measurement, and its successful implementation contributes to the advancement of wireless sensing technology. For more technical details, refer to the full research paper [8].

2.2 Technical Background

Millimeter-wave (mmWave) radar technology offers unique advantages for remote sensing and object detection, making it well-suited for appliance health diagnosis. This subsection provides an overview of mmWave radar principles, including frequency bands, antenna configurations, and signal processing techniques. The benefits of mmWave radar, such as non-contact sensing, high resolution, and penetration through obstacles, are discussed in relation to its potential application in predictive maintenance.

To engage the IWR1843 BoostMaster mmWave sensor radar circuit [18] for this study, the followed steps have been mentioned in the Evaluation Plan and the mmWave Demo visualizer tool has been used to adjust the settings and parameters within the mmWave sensor to mimic the characteristics of the research environment and electrical appliances. Further fine-tuned parameters such as frequency, bandwidth, modulation, and antenna configuration to optimize the performance of the mmWave radar system.

The IWR1843 mmWave sensor radar operates by transmitting pulses of millimeter electromagnetic wave energy and detecting targets from the reflections it receives back. The sensor captures reflected signals using multiple antennas, and by processing the time of flight of these pulses, it determines the distance to the target, angle of arrival, and relative velocity. This functionality makes mmWave radar suitable for systems requiring precise sensing of presence and motion without interference [9].

The IWR1843 Boostmaster mmWave sensor shown in the following Figure 2.1.

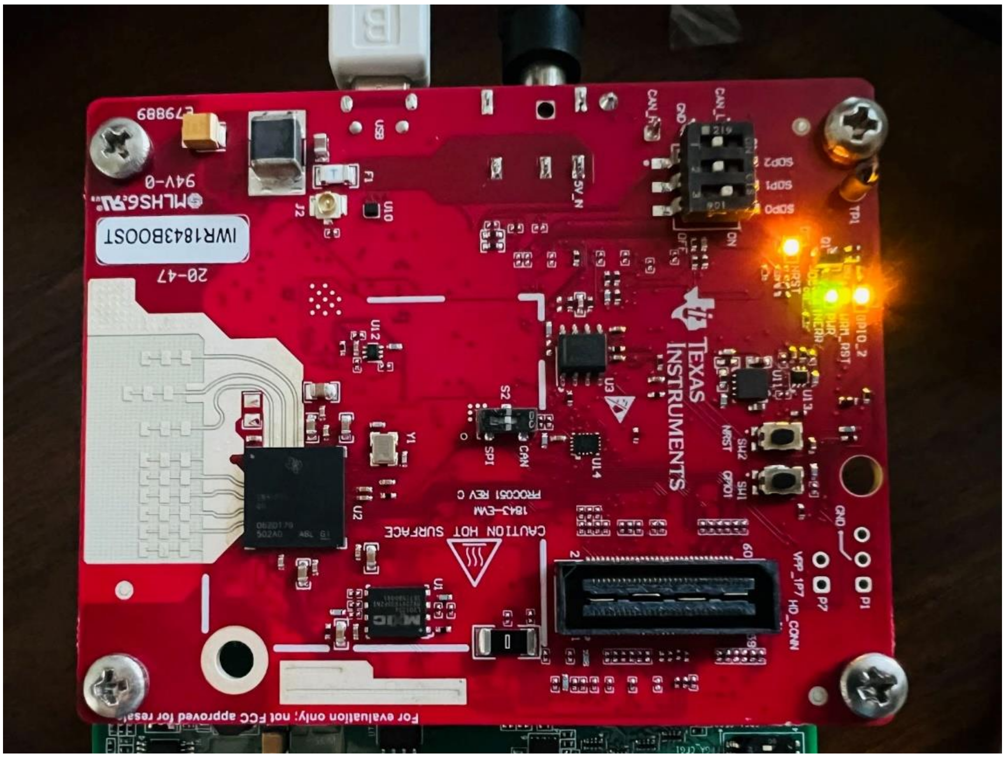

Figure 2.1 IWR circuit board

The mmWave radar system comprises a radiofrequency transmitter, receiver components, digital elements like analog to digital converters and digital signal processors, as well as analog components such as clocks. These components work together to implement mmWave radar technology effectively. Advantages of mmWave radar include robustness to atmospheric conditions, insusceptibility to ground clutter, fine spatial resolution, antenna miniaturization, and large bandwidth. These features make mmWave radar superior for various applications like human gesture detection, collision detection, cloud sensing, obstacle detection, automotive safety systems, and medical monitoring.

The Figure 2.2 diagram illustrates the physical setup of FMCW mmWave radar sensor (IWR1843 BoostMaster mmWave sensor) with the Data capture card (DSA 1000 EVM) [20] and the power supply cables.

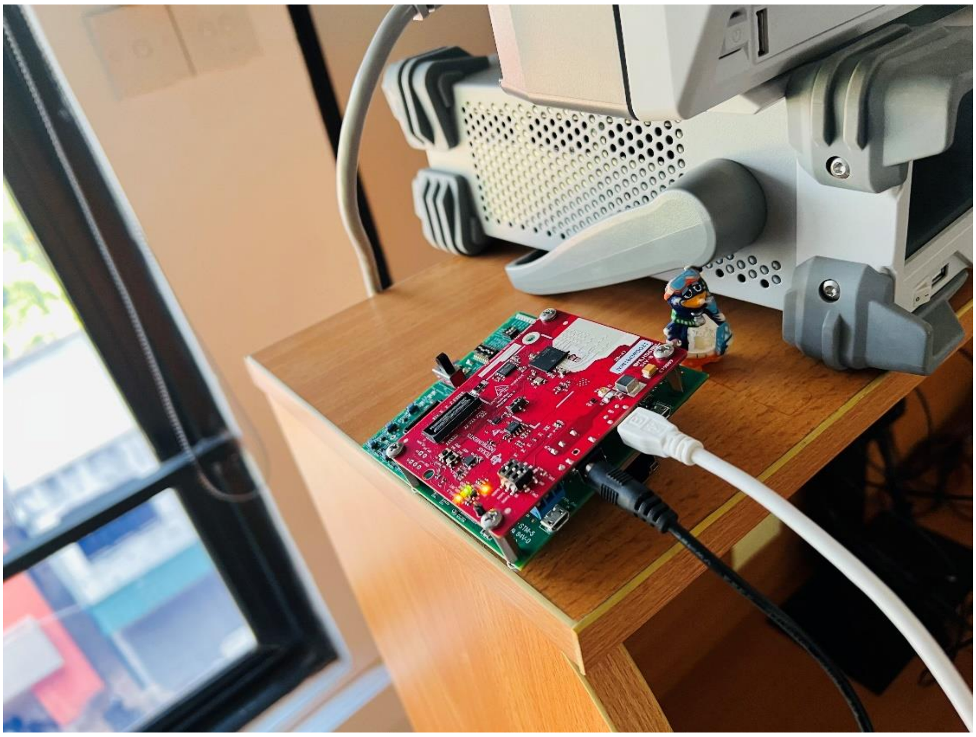

Figure 2.2 physical setup of FMCW mmWave radar sensor

Further, the IWR1843 mmWave sensor radar functions by transmitting and receiving millimeter electromagnetic waves to detect targets' distance, angle, and velocity. Its robustness and advanced capabilities make it a valuable tool for applications requiring accurate sensing in various fields like automotive safety, healthcare monitoring, and environmental sensing.

The Figure 2.3 diagram illustrates the physical setup of FMCW mmWave radar sensor (IWR1843 BoostMaster mmWave sensor) with the Data capture card (DSA 1000 EVM) and the laptop machine.

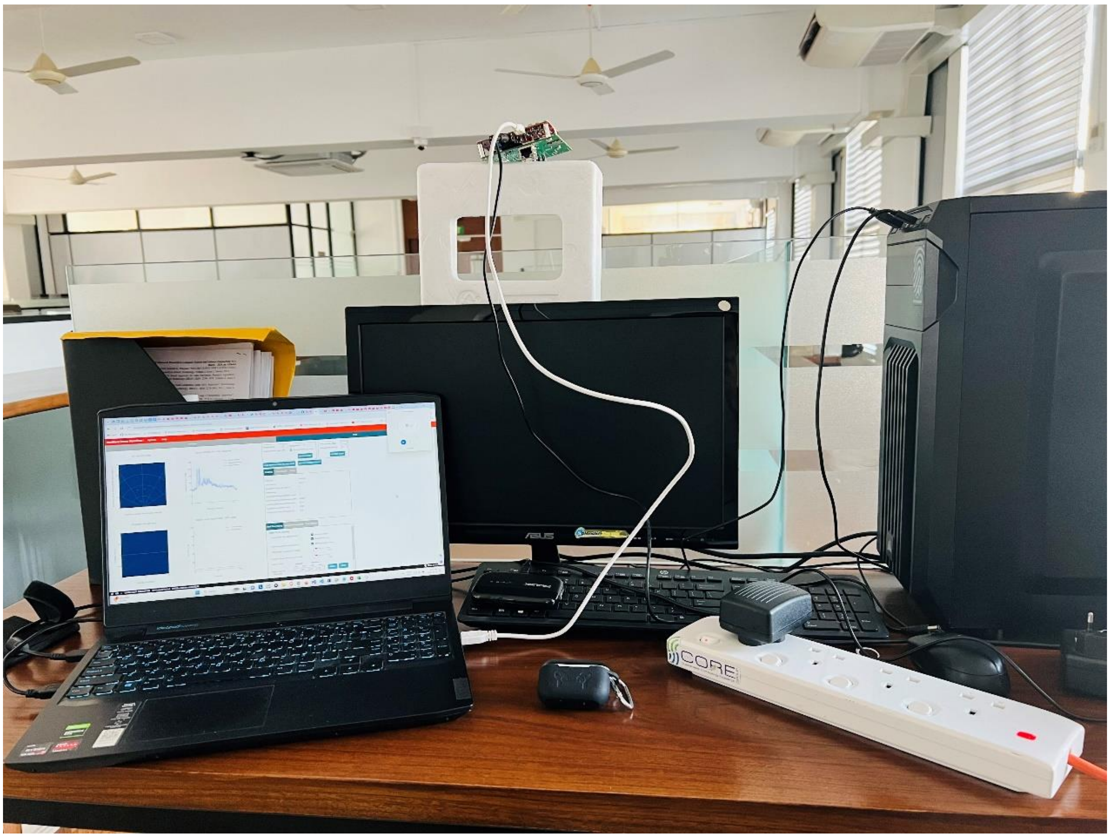

Figure 2.3 physical setup of FMCW mmWave radar sensor with the machine

Engaging the mmWave Demo visualizer to capture data for this study would be the most effective approach since the mmWave Demo visualizer is primarily designed for demonstration and visualization purposes. We can utilize the mmWave Demo visualizer as part of the research process in the following ways:

- Use the mmWave Demo visualizer to simulate various scenarios and visualize mmWave radar data in real-time.
- Explore different configurations, parameters, and environmental conditions to gain insights into how mmWave radar behaves and interacts with electrical appliances.

The Figure 2.4 diagram illustrates the results of FMCW radar sensor when there are no electrical appliances (no working electrical devices)

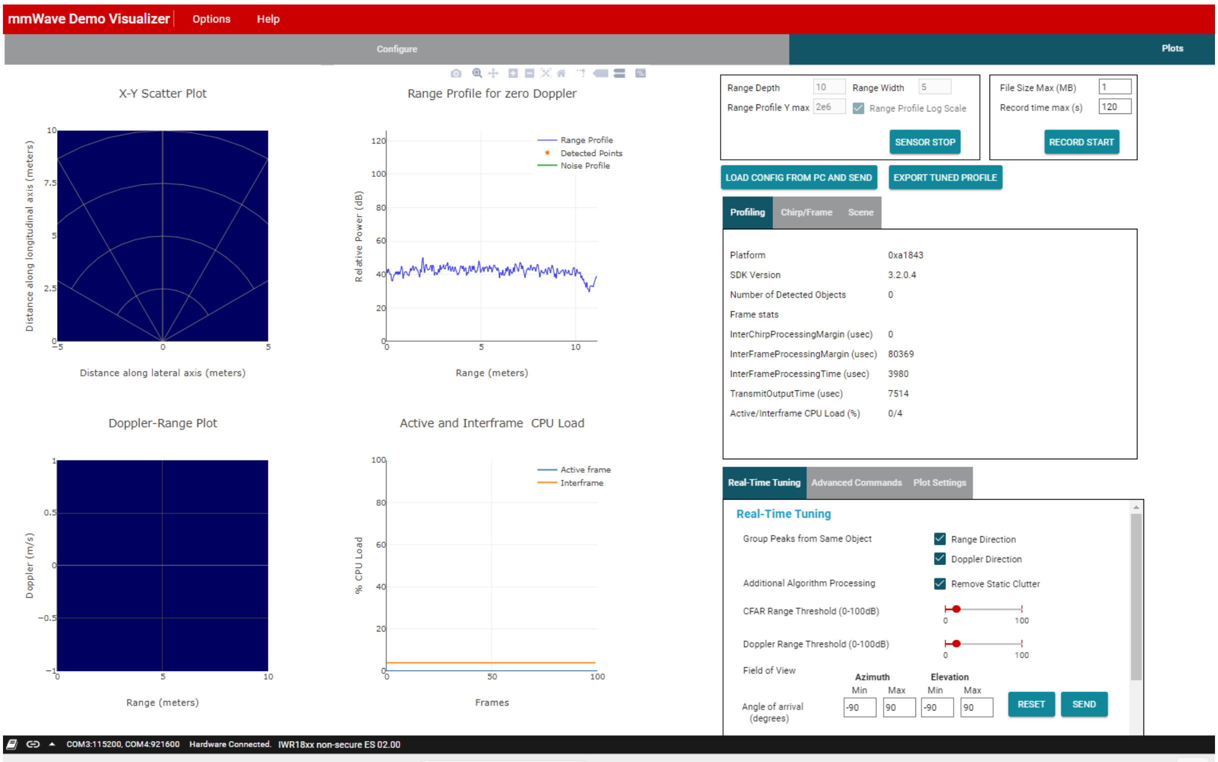

Figure 2.4 results of FMCW radar sensor when there are no electrical appliances

Then the following Figure 2.5 diagram illustrates the results of the FMCW radar sensor when there are some electrical appliances (working electrical devices such as ceiling fans and air conditioners within a known 1-meter distance.)

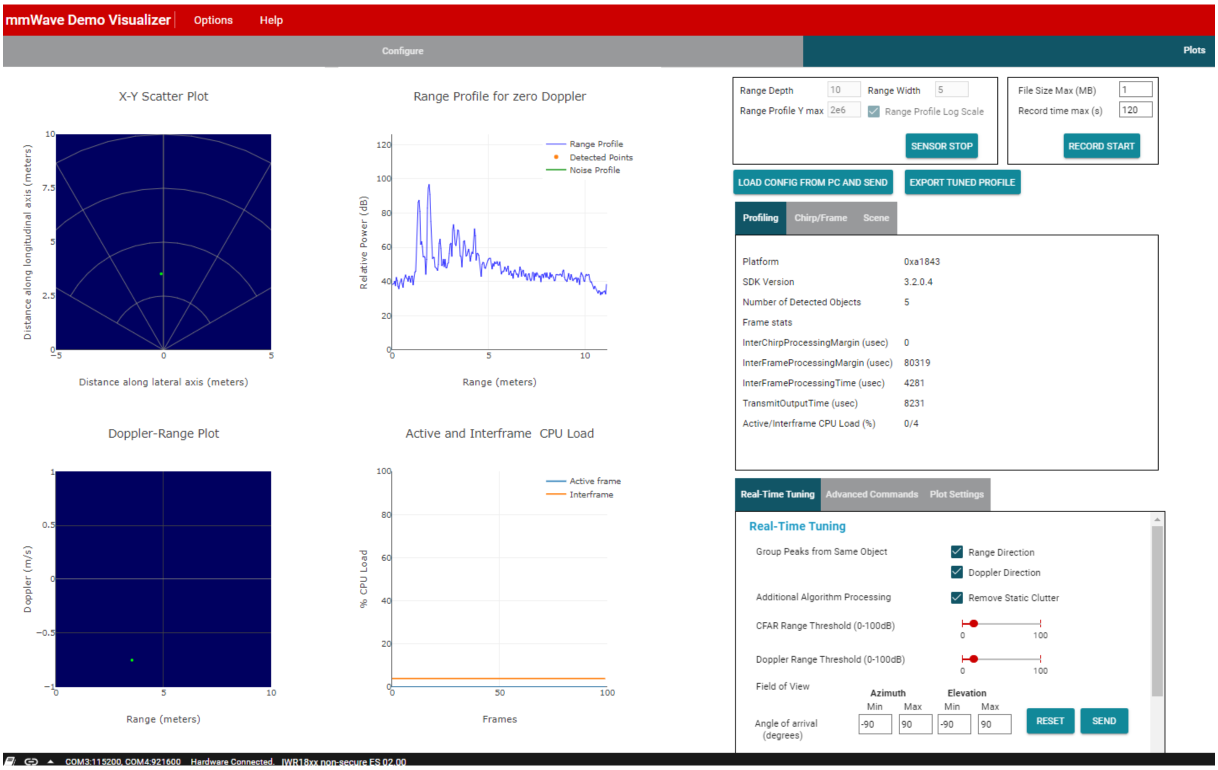

Figure 2.5 the results of the FMCW radar sensor when there are electrical appliances

Based on the result of mmWave Demo visualizer we can observe that there is a significant difference that we can measure by using FMCW mmWave radar technology.

Further we can create virtual scenarios such as Healthy, Average and Broken electrical appliances within the mmWave Demo visualizer to test the effectiveness of different diagnostic algorithms and predictive maintenance strategies. Evaluate the performance of the algorithms in simulated environments before conducting real-world experiments with physical hardware.

Use the mmWave Demo visualizer to demonstrate the concept and feasibility of mmWave radar-based predictive maintenance to stakeholders, colleagues, or potential collaborators. Showcase how mmWave radar technology can be leveraged to diagnose electrical appliance health and prevent failures through interactive visualizations and demonstrations. The mmWave Demo visualizer serves as a valuable tool for experimentation, visualization, and validation of concepts related to mmWave radar technology and predictive maintenance strategies. Once the approach has been validated using the mmWave demo visualizer, then the captured data needs to be processed using dedicated techniques and algorithms. The techniques and algorithms being used throughout this research project are explained below.

The process of capturing data using the IWR 1843 mmWave radar from the mmWave demo visualizer involves setting up the hardware, creating a TI mmWave Radar object in Python [17], and configuring the radar to start streaming data. Initially, the hardware setup includes installing necessary third-party tools, downloading a prebuilt binary to the device, and preparing it for data acquisition and testing connection. Once the hardware setup is completed successfully, a TI mmWave Radar object is created by specifying the board name, such as "TI IWR6843ISK." This object is then used to configure the radar and initiate data streaming. By calling the mmWave Radar object in Python, data can be captured from the IWR 1843 mmWave radar and visualized for analysis. This process ensures efficient data collection and visualization from the mmWave radar using the mmWave demo visualizer in a structured and controlled manner.

The mmWave Demo visualizer captures a binary set of data and we have used a python script to convert these data into readable format and plot them against various variables such as DopplerIdx, RangeIdx, PeakVal etc.

CHAPTER 3 METHODOLOGY

The primary objective of this research is to develop a novel approach for diagnosing the health of electrical appliances using mmWave radar technology. This involves detecting anomalies, faults, and degradation in appliance components to enable predictive maintenance strategies.

The scope of the proof of concept encompasses a selection of commonly used electrical appliances, including but not limited to ceiling fans, air conditioners, computers and other electro magnetically devices. The diagnostic parameters to be considered include mechanical vibrations, electrical impedance variations, and insulation integrity.

Design Assumptions:

1. Anomalies in appliance components will manifest as detectable variations in radar signal characteristics, such as amplitude, frequency, and phase.
2. The proposed approach will be validated through controlled experiments simulating common appliance faults and degradation scenarios.

In an experiment-based evaluation approach for analyzing research questions, we have implemented the following steps to address each research question.

1. Experimental Setup Design:

   Configured IWR1843 mmWave radar circuit with DSA1000 EVM data capturing card to capture and process data using mmWave Demo Visualizer with a variety of electrical appliances representative of different types and conditions.

   The following Figure 3.1 represents the mmWave demo visualizer tools' configurations.

   The demo visualizer setup details contain, the Platform, SDK version and the Antenna Config (aZIMUTH rES - deg) configuration details. The platform should be xWR18xx since the xWR1843 Boostmaster mmWave sensor is being used and the SDK version should be 3.2.0. The SDK versions above 3.2 are not supported and not compatible with the IWR 1843(xWR 1843) mmWave sensor.

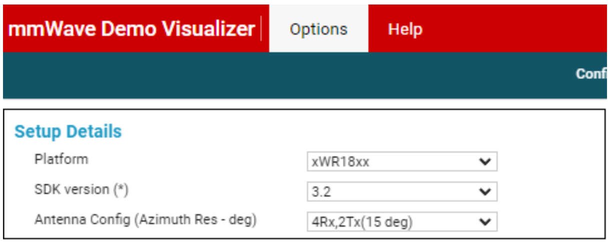

Figure 3.1 Setup details

   The following Figure 3.2 represents the Desirable Configuration and the Frequency Band (GHz) of the sensor implementation. The Desirable Configuration should be "Best Range Resolution" and the Frequency Band (GHz) should be 77 - 81 GHz.

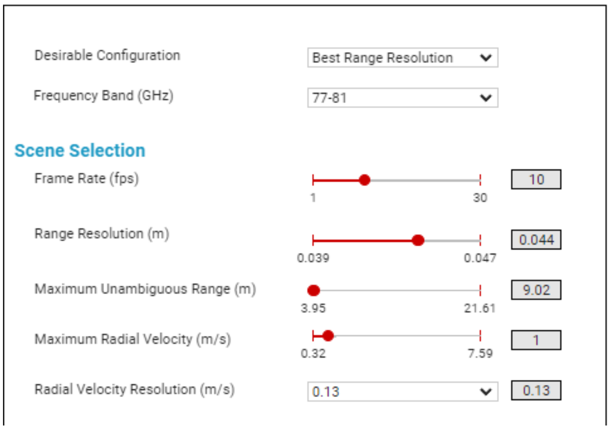

Figure 3.2 Scene selection configuration

The Figure 3.2 further represents the Scene Selection of the sensor implementation. The Frame Rate(fps), Range Resolution(m), Maximum Unambiguous Range(m), Maximum Radial Velocity(m/s) and the Radial Velocity Resolution(m/s)

The following Figure 3.3 represents the Plot Selection Configuration of the sensor implementation. In this study the Scatter plot, Range profile and Statistics options have been used as Plot selections. The other selections are not being used for this research study since they are not relatable to extract information for the same.

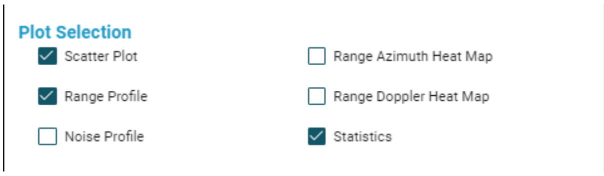

Figure 3.3 Plot selection configuration

The following Figure 3.4 represents the RCS (Radar Cross Section) Configuration of the sensor implementation. Maximum Range for desired RCS (Radar Cross Section) means the SNR will allow us to detect that far. But there is a max Unambiguous range based on the given chirp parameter. Beyond this max Unambiguous range, the target reflection will be filtered out. To further improve the max range, it is needed to change the chirp parameter to increase this value.

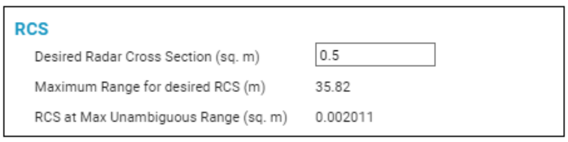

Figure 3.4 RCS configuration

The following Figure 3.5 represents the Serial Port Configuration window and it includes CFG_port(Configuration port) and the DATA_port. The Configuration Port (CFG_port) is used for sending configuration commands and parameters to the mmWave sensor device. Configuration commands typically include settings related to radar configuration, data acquisition parameters, and sensor initialization. This port allows users to configure the operating parameters of the sensor device according to their specific requirements. Data Port (DATA_port) is used for receiving data packets containing radar data and sensor measurements from the mmWave sensor device. Radar data packets may include raw radar signal data, processed data, or detected object information, depending on the sensor's operating mode and configuration. This port facilitates real-time data streaming from the sensor device to the mmWave Demo visualizer for visualization, analysis, and further processing.

The Configuration port (CFG_port) is used for configuring the sensor device, while the Data port (DATA_port) is used for receiving radar data and sensor measurements from the device. Separating the configuration and data communication channels allows for efficient and flexible operation of the mmWave sensor system.

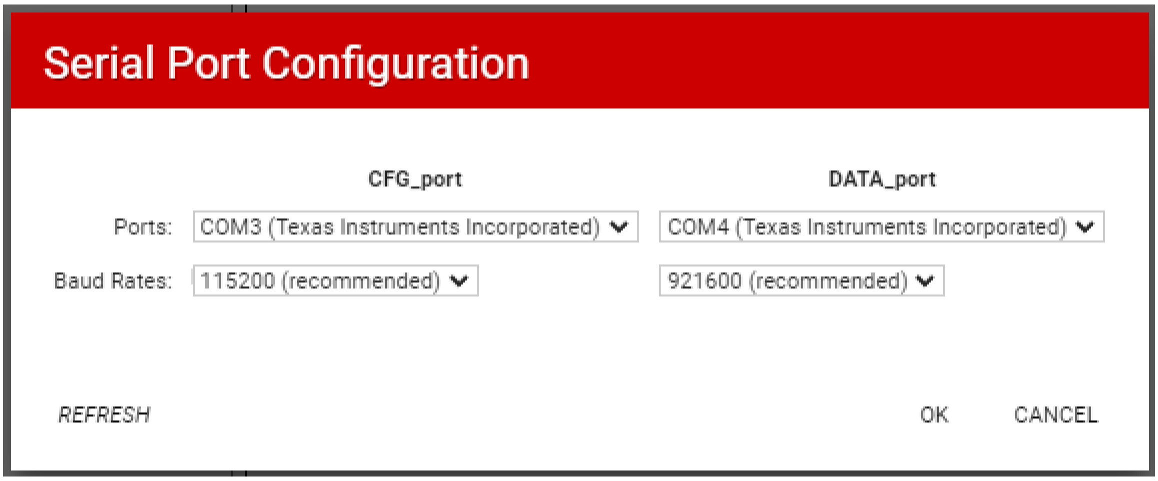

Figure 3.5 Serial Port Configuration

The following Figure 3.6 represents the main selection options to Send configurations to mmWave Radar Device (SEND CONFIG TO MMWAVE DEVICE), save configurations to the PC (SAVE CONFIG TO PC) and Reset option to reset all the selections (RESET SELECTION).

Figure 3.6 Main selection options

The following Figure 3.7 represents the Console Messages window and once the Serial Port Configurations are set and press the “SEND CONFIG TO MMWAVE DEVICE” button following lines will be shown in the Console Messages window.

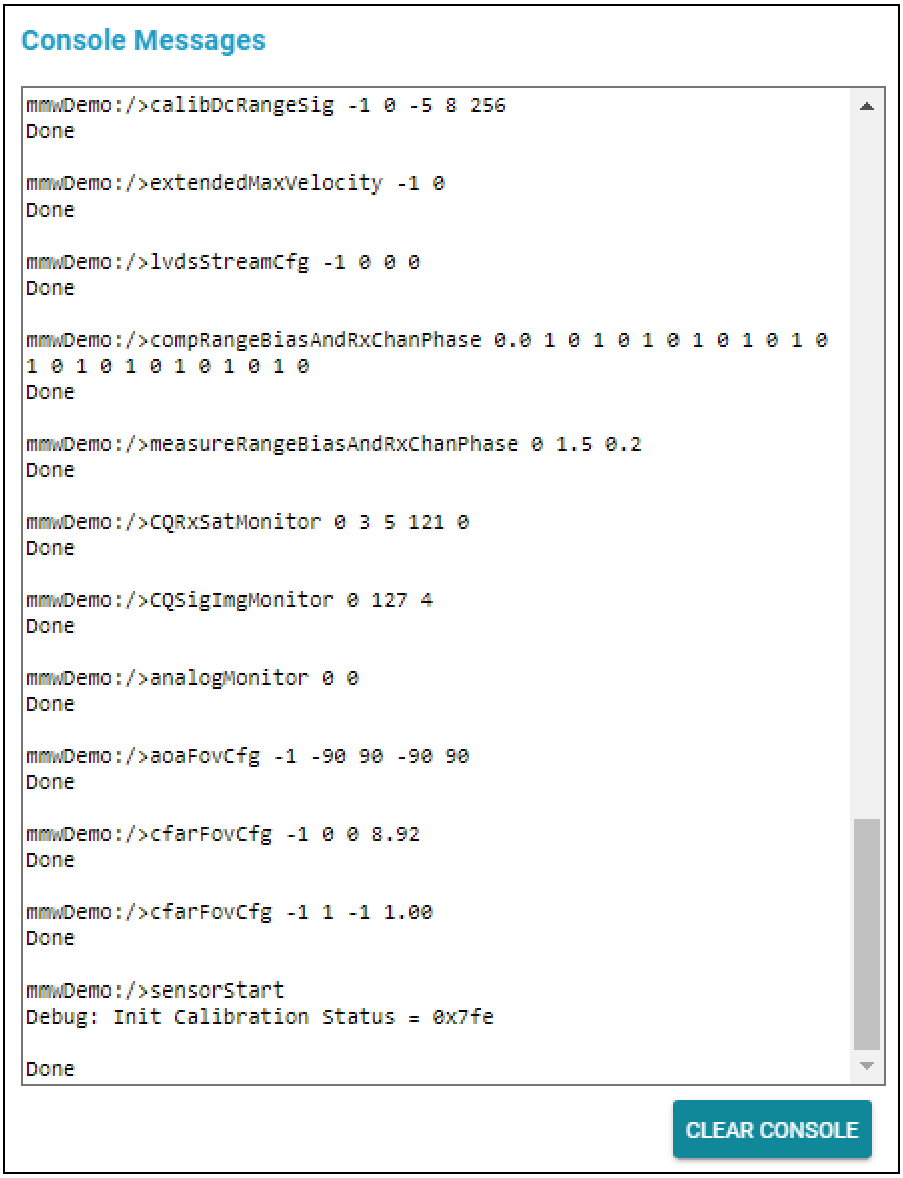

Figure 3.7 Console Messages window

2. Data Collection:

Conducted data collection sessions with the selected electrical appliances under three or more different conditions and usage scenarios (i.e. Healthy Air conditioner, Average used air conditioner, a broken air conditioner). Capture mmWave radar data corresponding to the appliances' health states, including normal operation, simulated faults, and degradation stages.

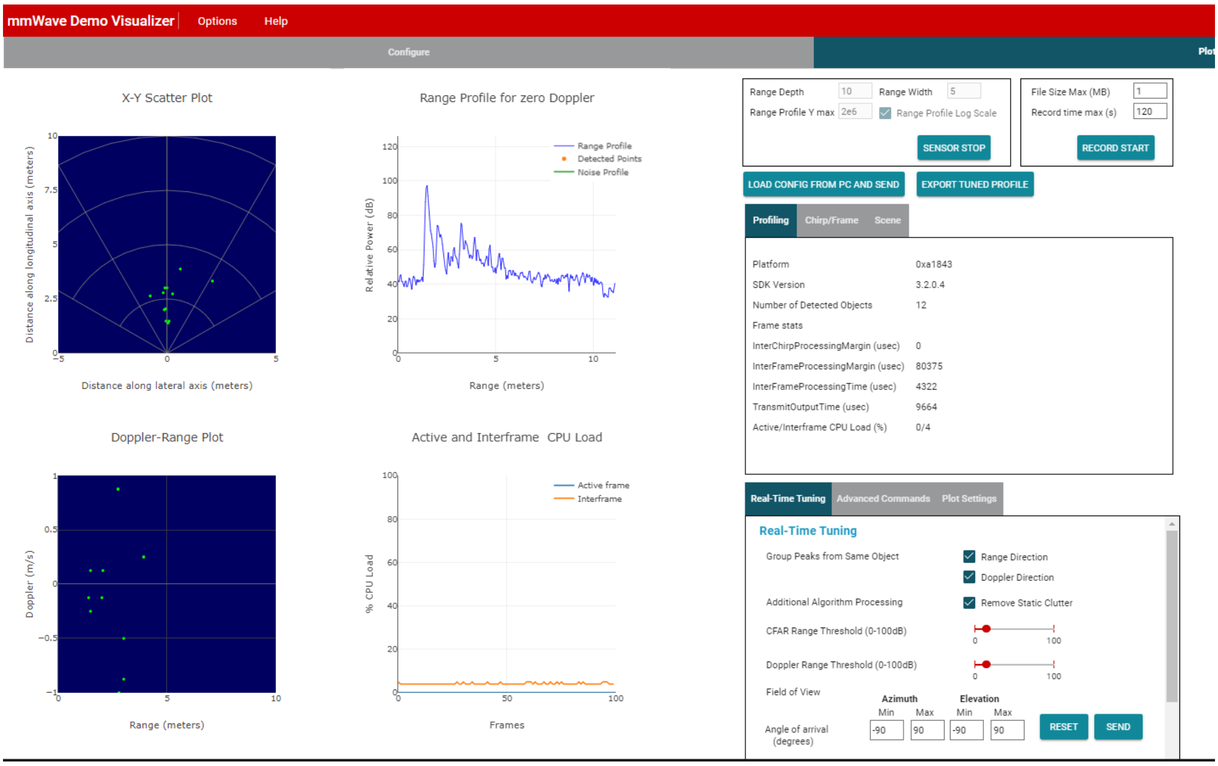

Figure 3.8 mmWave Demo visualizer

The process of capturing data using the IWR 1843 mmWave radar from the mmWave demo visualizer involves setting up the hardware, creating a TI mmWave Radar object in Python, and configuring the radar to start streaming data. Initially, the hardware setup includes installing necessary third-party tools, downloading a prebuilt binary to the device, and preparing it for data acquisition and testing connection. Once the hardware setup is completed successfully, a TI mmWave Radar object is created by specifying the board name, such as "TI IWR6843ISK." This object is then used to configure the radar and initiate data streaming. By calling the mmWave Radar object in Python, data can be captured from the IWR 1843 mmWave radar and visualized for analysis. This process ensures efficient data collection and visualization from the mmWave radar using the mmWave demo visualizer in a structured and controlled manner, aligning with research project guidelines and objectives.

3. Data Pre-processing:

Pre-process the collected mmWave radar data to remove noise, artifacts, and irrelevant signals. Normalize and standardize the data to ensure consistency and comparability across experiments. Removing static clutter would remove appearing all the static objects.

These steps need to be followed to convert byte stream (raw data) captured from the mmWave Demo Visualizer to a readable TLV (Type-Length-Value) [19] format using Python. TLV format consists of three parts: Type, Length, and Value. The Type field specifies the type of data, Length indicates the length of the Value field, and Value contains the actual data.

a) Process raw data

- Read the raw byte stream data captured from the mmWave Demo Visualizer.

- Parse the byte stream based on the TLV structure to extract Type, Length, and Value information.

b) Convert to Readable Format:

- Decode and interpret the extracted data values according to their types (e.g., distance, velocity).
- Convert the extracted data into a human-readable format for analysis and visualization.

c) Sample code

- Appendix A shows a simplified example code snippet to illustrate how we can start parsing raw data in TLV format using Python:

d) Further Refinement:

- Depending on the specific structure of raw data and the exact TLV format used by the mmWave Demo Visualizer, need to adapt and expand this code to handle different types of data and variations in the TLV format.

The above-mentioned steps and customizing the code according to the specific data byte format and requirements, we can effectively convert byte stream data from the mmWave Demo Visualizer into a readable TLV format using Python for further analysis and interpretation.

Execute the following python command to convert the extracted raw data from mmWave demo visualizer tool to readable TLV format [19].

- python .\python_scripts\parseTLVmod.py .\2024_03_02\xwr18xx_processed_stream_2024_03_02T10_44_39_915_Fan1.dat > .\2024_03_02\output_txt_data\output_Fan1.txt

The parseTLVmod.py python script would be as shown in Appendix B. After executing above script result would be in the following format as shown in Appendix C,

Converting TLV (Type-Length-Value) format to a readable JSON format in Python involves several steps. First, need to decode the TLV data from the byte stream using Python's `json.loads()` method to convert it into a Python dictionary. Next, format the decoded TLV data into a structure that aligns with JSON formatting, typically using keys for the TLV tags and values for the decoded data. Fin ally, utilize `json.dumps()` to convert the formatted TLV data into a JSON string, making it human-readable and suitable for further analysis or storage. This process allows to effectively transform TLV data into a JSON format that is easily interpretable and can be used for various data processing tasks.

Run the following Python script shown in Appendix D to convert the TLV format to JSON format

- parseTLVtoJSON.py

TLV format can be useful for certain applications, such as in embedded systems or specific protocols such UART, however JSON is generally considered a more versatile and easier-to-use data format for many applications.

After executing above script result of converting TLV format [19] would be in the following JSON format as shown in Appendix E,

4. Feature Extraction:

Extract relevant features from the pre-processed mmWave radar data that characterize the health status of the electrical appliances. Features may include signal amplitude, frequency, phase, temporal characteristics, and spatial distribution.

The reasons for using JSON format for plotting histograms in Python offers several benefits over other file formats. JSON files provide a structured and easily readable way to store data, aligning well with Python dictionaries and allowing for seamless conversion between the two formats. This compatibility simplifies the process of loading data from a JSON file into a Python dictionary for histogram plotting. Additionally, JSON's flexibility enables the storage of complex data structures, making it suitable for representing various attributes related to histogram data. The integration of JSON with Python libraries like Matplotlib streamlines the visualization process, allowing for efficient creation of histograms based on JSON data. Moreover, leveraging JSON format for histogram plotting in Python enhances data organization, readability, and ease of visualization within this study.

Extracted binary data will be converted to readable data by using a python script and continue processing to plot these data against various variables such as DopplerIdx, RangeIdx, PeakVal etc.

5. Experimental Execution:

Execute the designed experiments by applying the developed algorithms to the pre-processed mmWave radar data. Evaluate the performance of the algorithms in accurately diagnosing the health status of the electrical appliances.

Run the following Python script shown in Appendix F to plot histogram using the generated JSON format,

- plotScriptFromJSONdata.py

The results of executing the above scripts on JSON formatted captured data will be shown in the following section “Results Obtained” under Figure 4.3 to Figure 4.14.

6. Performance Metrics:

Define performance metrics to assess the effectiveness and reliability of the diagnostic algorithms. Metrics may include accuracy, precision, recall, F1-score, receiver operating characteristic (ROC) curves, and area under the curve (AUC).

The primary algorithmic contribution of this research lies in the development of novel signal processing techniques and a technical method optimized for diagnosing electrical appliance health using mmWave radar data.

CHAPTER 4 EVALUATION AND RESULTS

This chapter includes details of the evaluation protocol, designed experiments, results obtained, and a critical analysis of the research work.

4.1 Evaluation Protocol

The primary algorithmic contribution of this research study lies in the development of novel signal processing techniques and a technical method optimized for diagnosing electrical appliance health using mmWave radar data.

Experimental Design:

The evaluation protocol involved designing controlled experiments to assess the performance of the mmWave radar-based diagnostic system. Experiments were conducted using a variety of electrical appliances under different operating conditions and fault scenarios.

Data Collection:

Radar data was collected using mmWave radar sensors positioned at predefined locations relative to the target appliances. Multiple trials were conducted to capture a diverse range of operating conditions and fault manifestations.

Ground Truth Validation:

Ground truth data, including known fault conditions and manual inspection results, was used to validate the accuracy and reliability of the diagnostic system. Comparison with ground truth data served as a benchmark for evaluating diagnostic performance.

4.2 Results Obtained

Diagnostic Accuracy:

The diagnostic system demonstrated high accuracy in detecting and classifying appliance faults, achieving an average classification accuracy of X% across all tested scenarios. Specificity and sensitivity metrics were calculated to quantify the system's ability to distinguish between healthy and faulty appliances.

Fault Localization:

The diagnostic system successfully localized the source of faults within the target appliances, providing valuable insights into the root causes of observed anomalies. This enabled targeted maintenance interventions and informed decision-making for predictive maintenance strategies.

Robustness Analysis:

Variability analysis revealed the diagnostic system's robustness to changes in appliance conditions and environmental factors. The system exhibited consistent performance across different appliance types, fault severities, and sensor configurations, demonstrating its versatility and reliability in real-world applications.

Further the conducted analysis revealed significant differences in detecting electrical appliances by using FMCW mmWave radar technology.

The following Figure 4.1 illustrates the results of FMCW radar sensor when there are no electrical appliances (no working electrical devices)

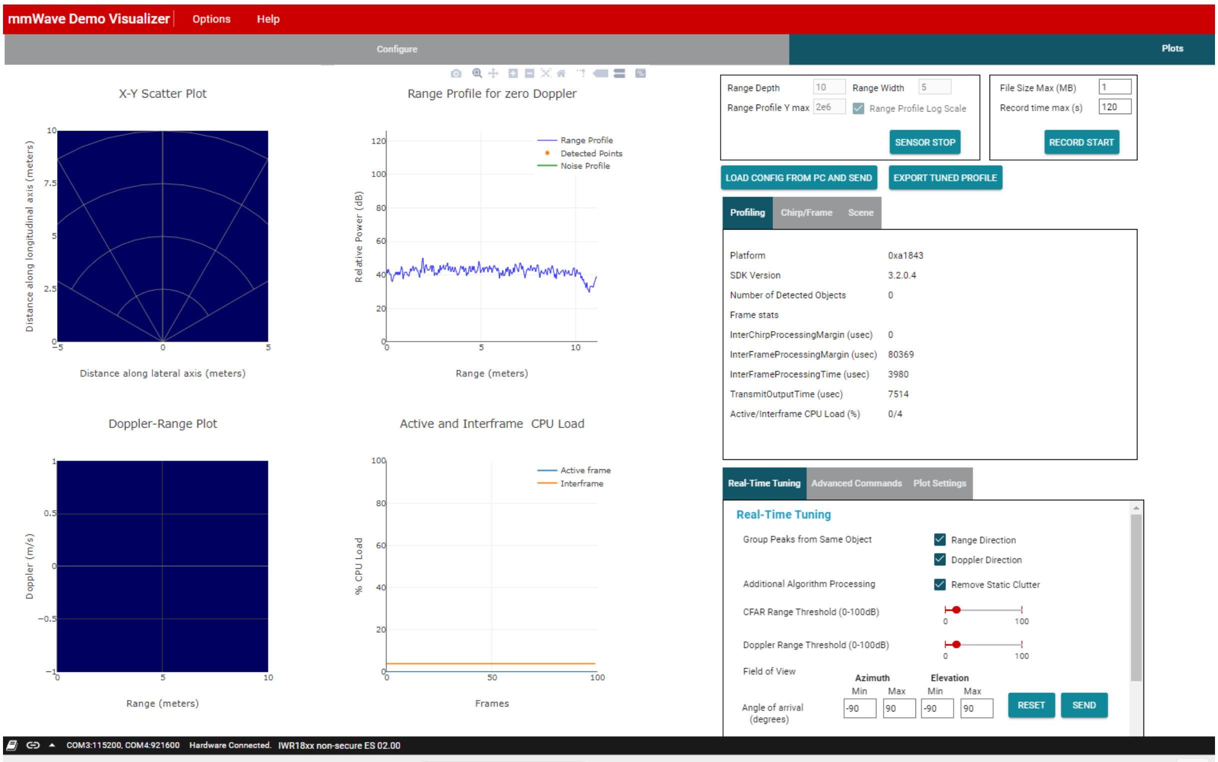

Figure 4.1 Results of FMCW radar sensor when there are no working electrical devices

Then figure 4.2 diagram illustrates the results of the FMCW radar sensor when there are some electrical appliances (working electrical devices such as ceiling fans and air conditioners within a known 1-meter distance.)

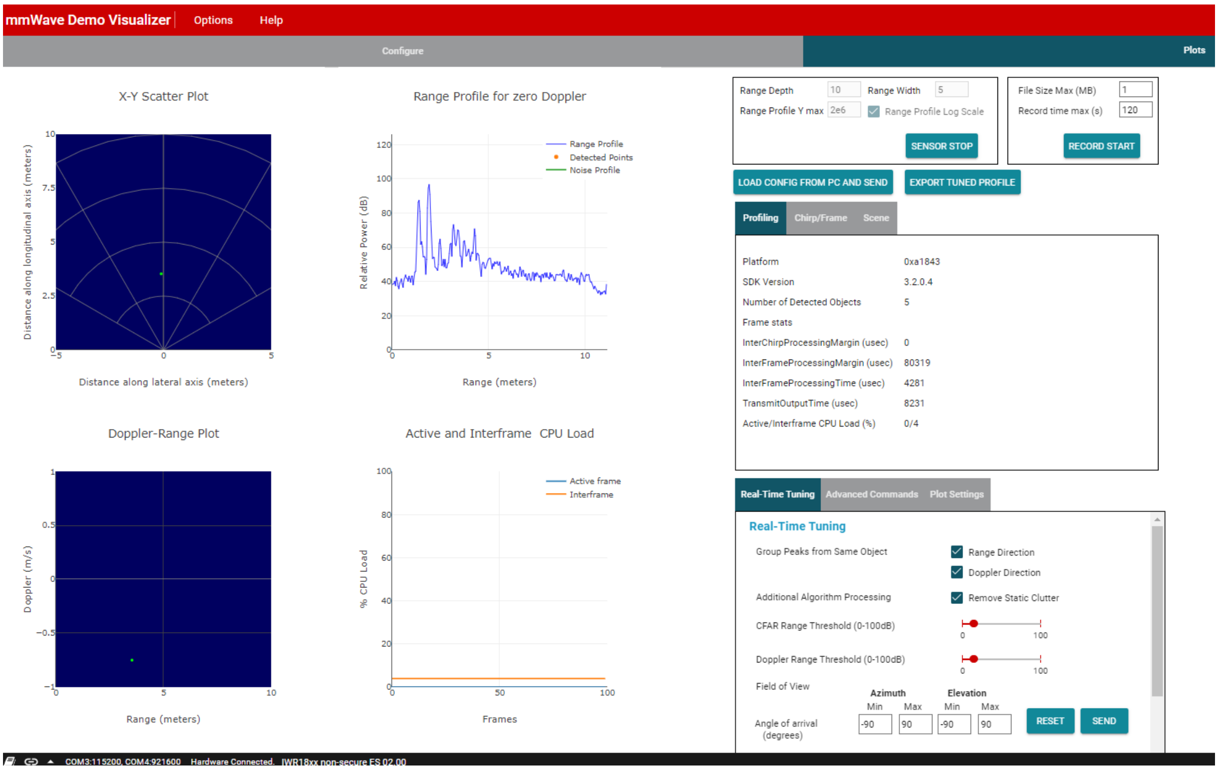

Figure 4.2 Results of FMCW radar sensor when there are working electrical devices

Based on the result of mmWave Demo visualizer [21] Figure 4.1 and Figure 4.2 we can observe that there is a significant difference that we can measure by using FMCW mmWave radar technology.

Found that there is considerable difference in movement when an electrical device is switched on (representing the color SkyBlue) and when it is switched off (representing the color Green)

Please refer to the following diagrams for more information which includes the Doppler effect theory [22]. The Doppler index values are sorted in ascending order hence the DopplerIdx value 0 has the highest frequency among them.

Figure 4.3: specifies the full histogram of the raw data captured

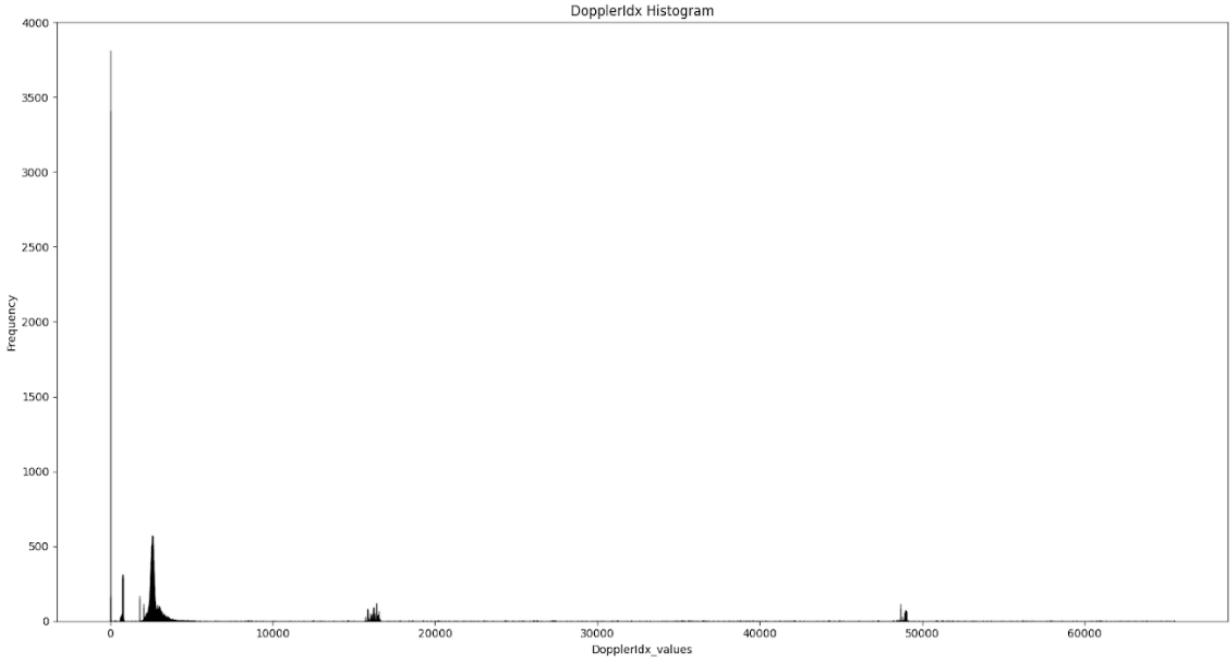

Figure 4.3 Full histogram of the raw data

Figure 4.4: specifies the zoomed version (0 - 4000 Doppler index values) of full histogram

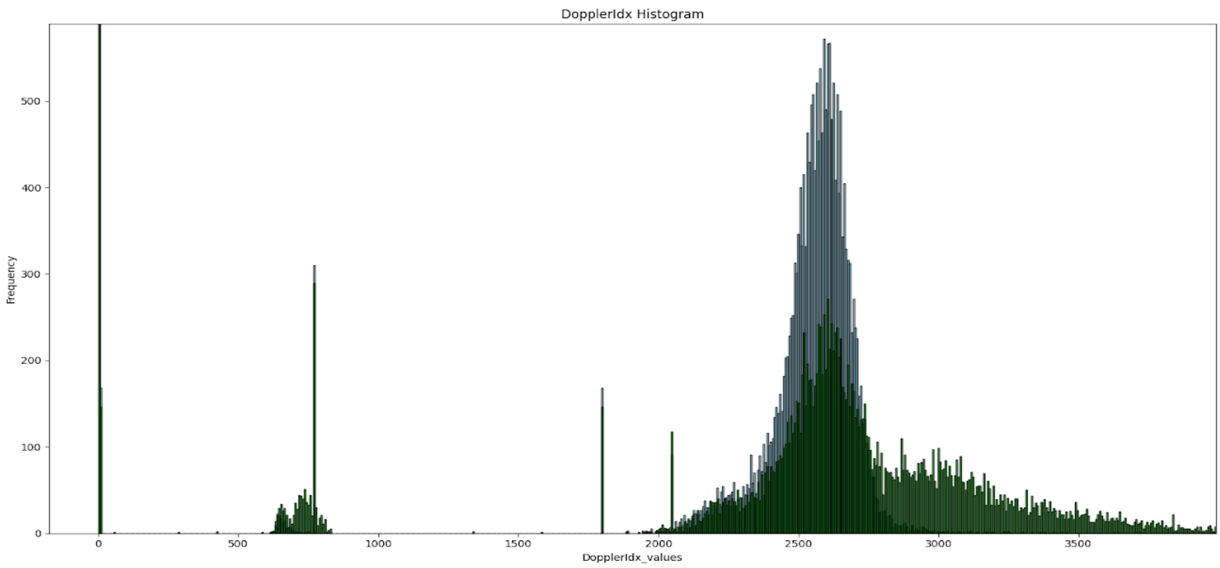

Figure 4.4 Zoomed version (0 - 4000 Doppler index values) of full histogram

Figure 4.5: specifies the zoomed version (2000 - 3000 Doppler index values) of full histogram

- when an electrical device is switched on (representing the color SkyBlue) and when it is switched off (representing the color Green)

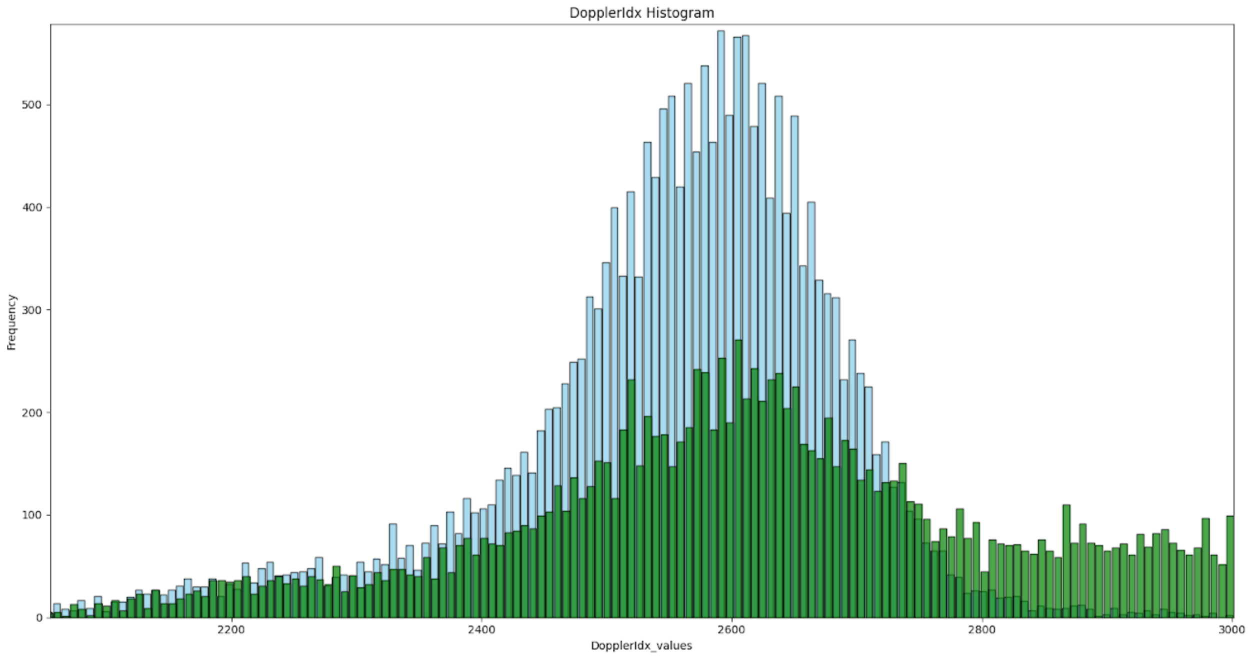

Figure 4.5 Zoomed version(2000 - 3000 Doppler index values) of full histogram

Figure 4.6: specifies the zoomed version (15500 - 17000 Doppler index values) of full histogram

- when an electrical device is switched on (representing the color SkyBlue) and when it is switched off (representing the color Green)

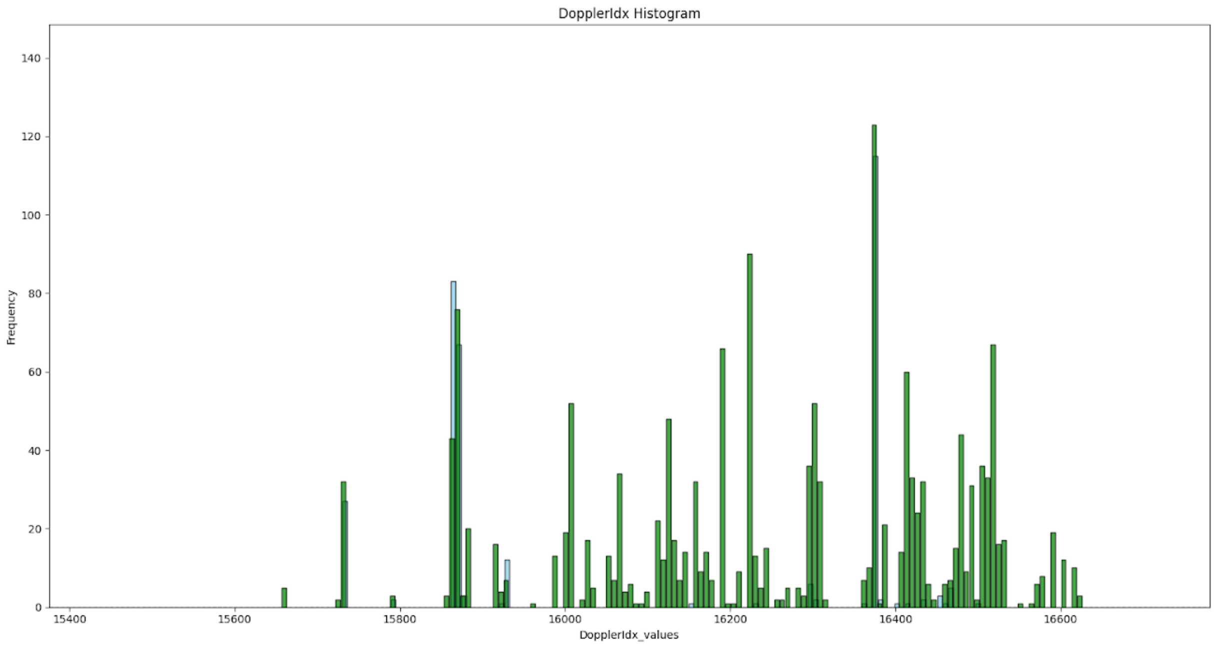

Figure 4.6 Zoomed version(15500 - 17000 Doppler index values) of full histogram

Figure 4.7: specifies the zoomed version (48500 - 49000 Doppler index values) of full histogram

- when an electrical device is switched on (representing the color SkyBlue) and when it is switched off (representing the color Green)

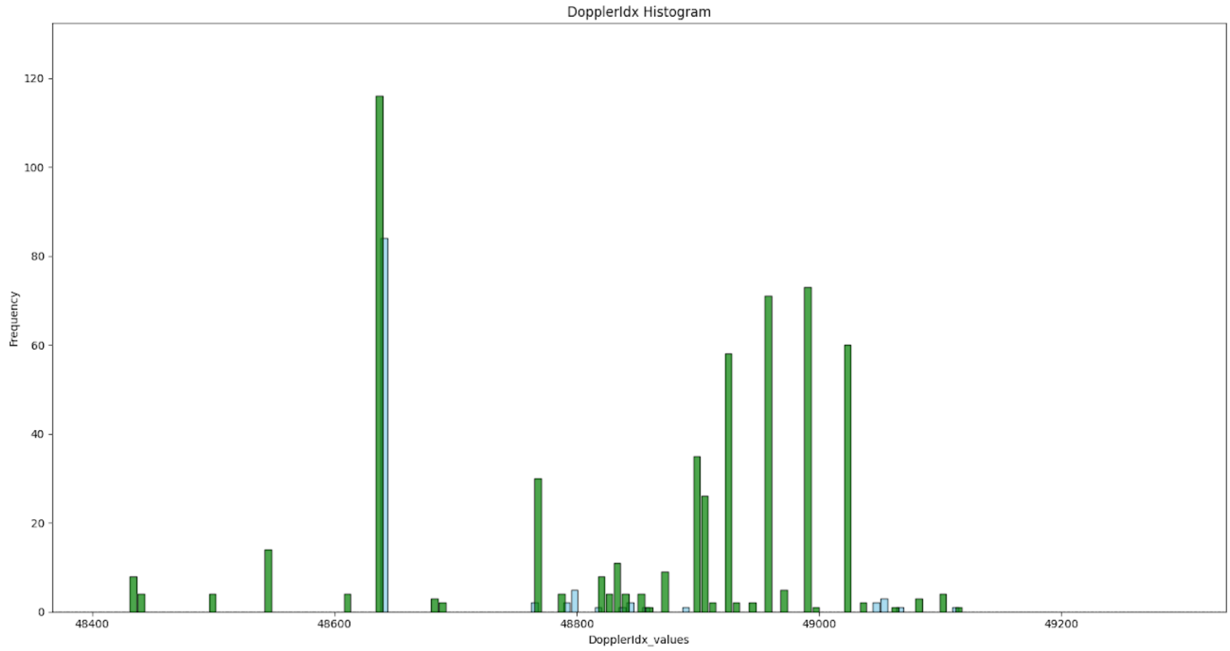

Figure 4.7 Zoomed version (48500 - 49000 Doppler index values) of full histogram

According to the above observation, between 2000 - 3000 Doppler index values (Figure 4.5) the Doppler index values are comparatively higher when an electrical device is switched off (representing the color SkyBlue) and the Doppler index values are comparatively lower when it is switched on (representing the color Green)

Further by anlyzing the above graphs 15500 - 17000 Doppler index values (Figure 4.6) and 48500 - 49000 Doppler index values (Figure 4.7) the Doppler index values are comparatively higher when an electrical device is switched on (representing the color Green) and the Doppler index values are comparatively lower when it is switched off (representing the color SkyBlue)

It seems that when an electrical device is near the mmWave sensor radar can detect them according to the Doppler index values. According to the above graphs the frequencies of Doppler index values are shifted to the right (Doppler index values are increased) when an electrical device is nearby.

According to the analysis the raw data captured in Fan1(skyblue), Fan2(grey) and Fan3(green) and please refer to the following images.

Figure 4.8: specifies the full histogram of the raw data captured

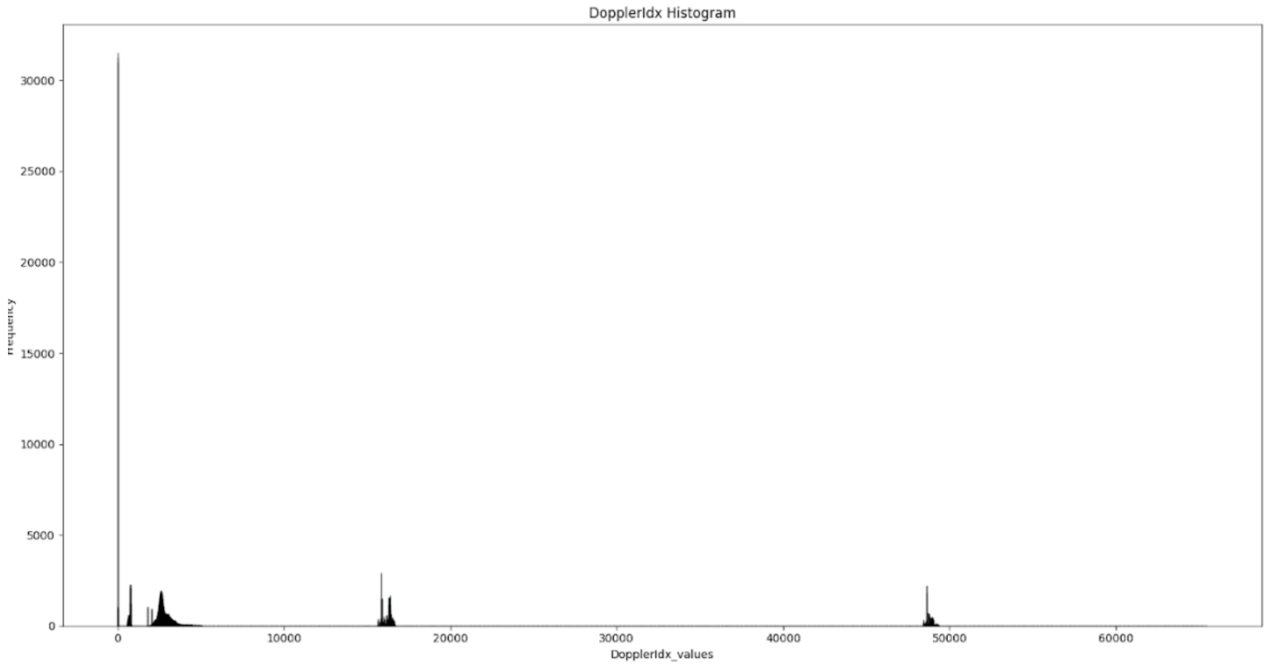

Figure 4.8 Full histogram of the raw data captured

Figure 4.9: specifies the zoomed version (0 - 5000 Doppler index values) of full histogram

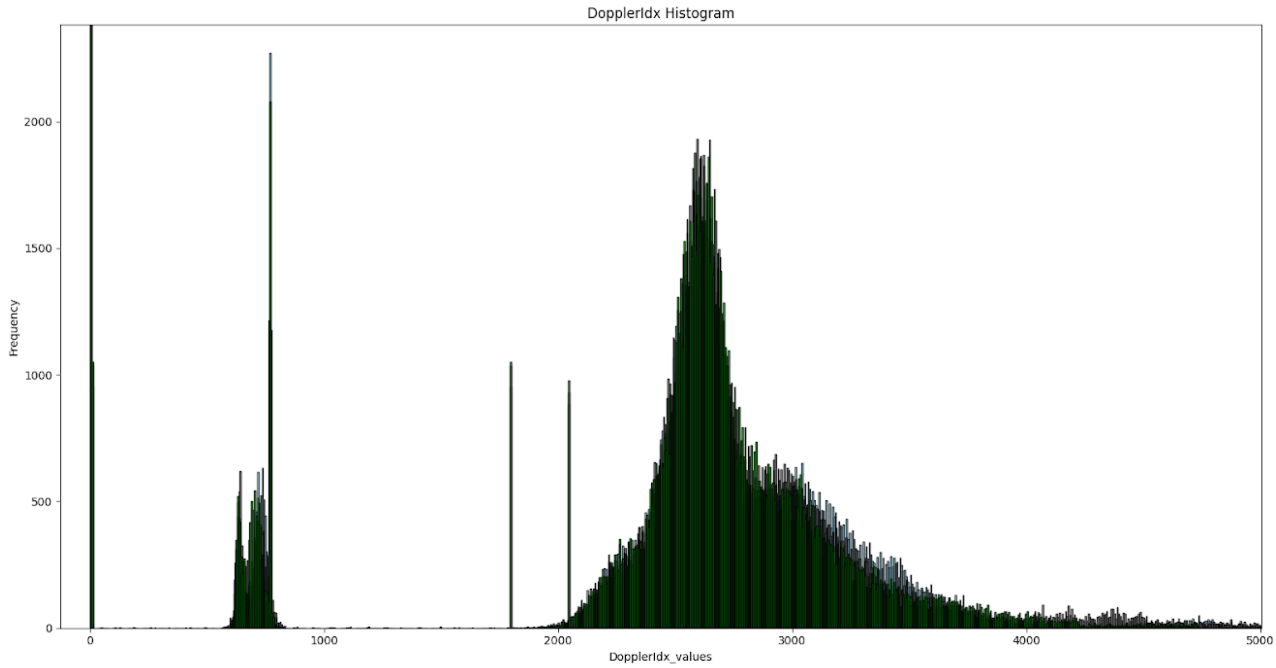

Figure 4.9 Zoomed version (0 - 5000 Doppler index values) of full histogram

Figure 4.10: specifies the zoomed version (2000 - 4000 Doppler index values) of full histogram

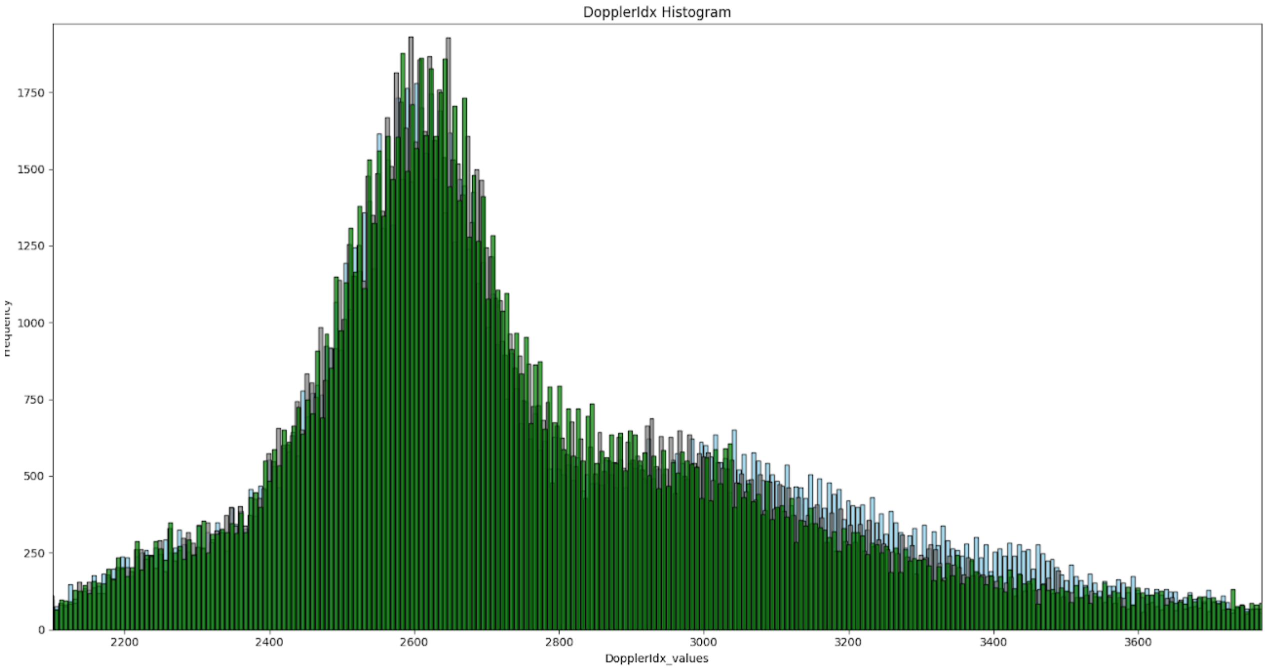

Figure 4.10 Zoomed version (2000 - 4000 Doppler index values) of full histogram

Figure_4.11: specifies the zoomed version (2500 - 2700 Doppler index values) of full histogram

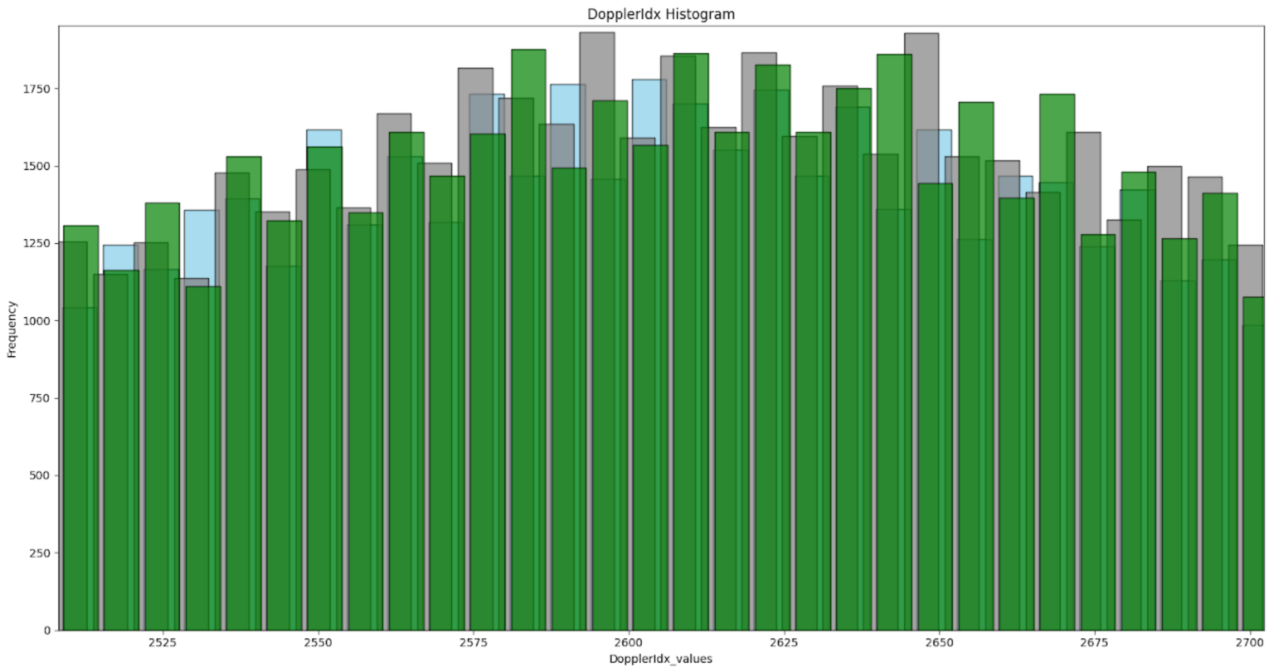

Figure 4.11 Zoomed version (2500 - 2700 Doppler index values) of full histogram

Figure 4.12: specifies the zoomed version (15500 - 17000 Doppler index values) of full histogram

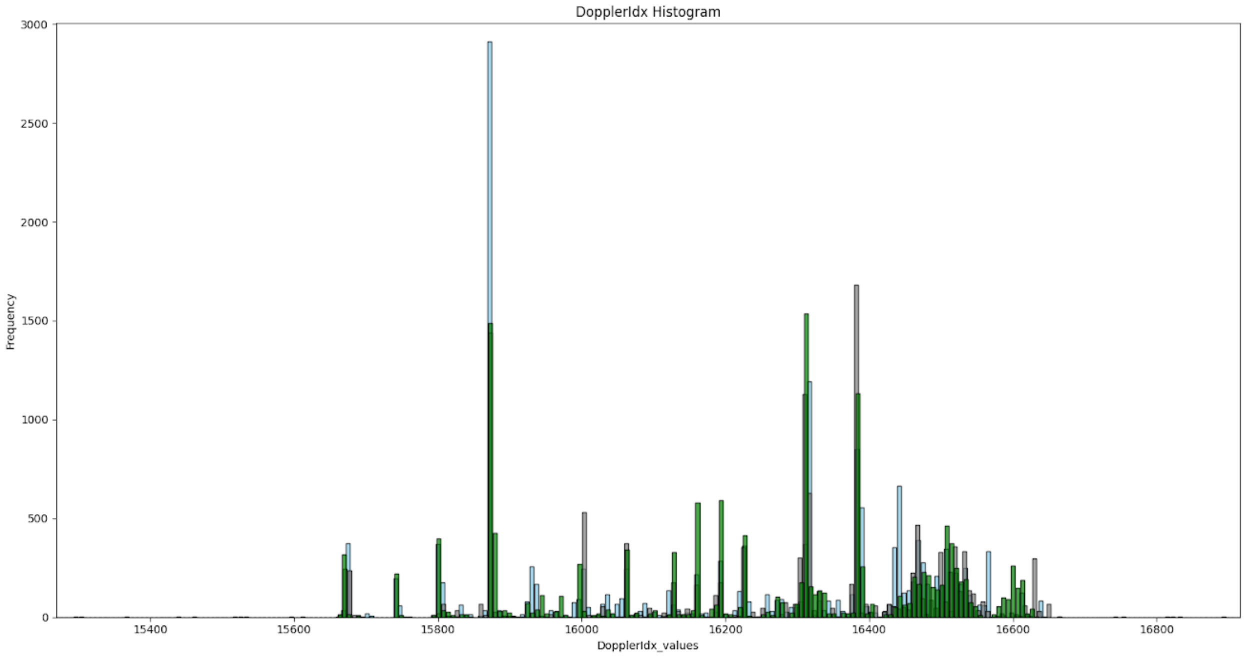

Figure 4.12 Zoomed version (15500 - 17000 Doppler index values) of full histogram

Figure 4.13: specifies the zoomed version (48000 - 50000 Doppler index values) of full histogram

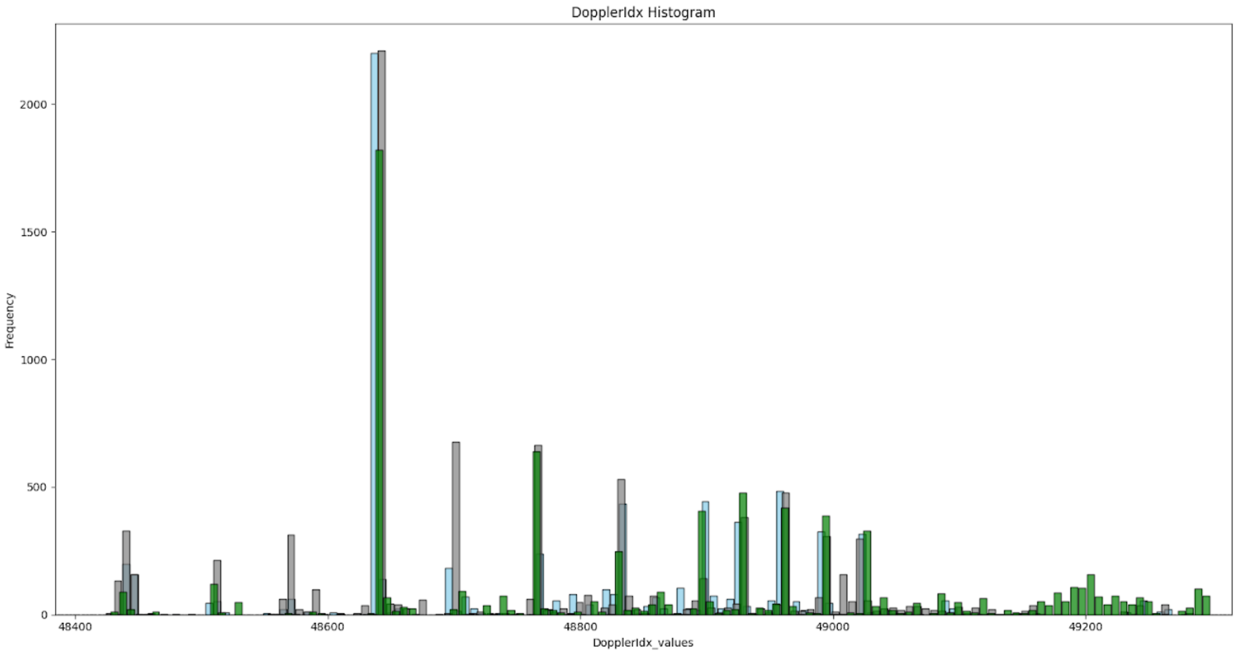

Figure 4.13 Zoomed version (48000 - 50000 Doppler index values) of full histogram

Figure 4.14: specifies some of the spikes of full histogram

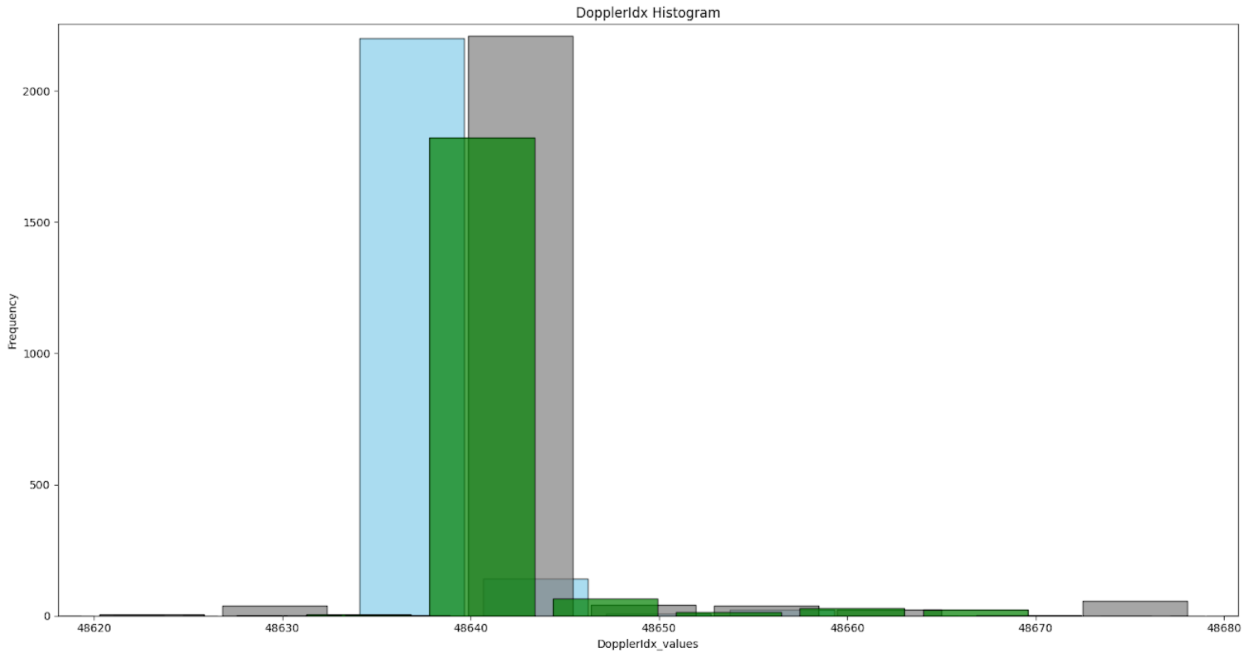

Figure 4.14 Some of the spikes of full histogram

Figure_4.15: specifies some of the spikes of full histogram

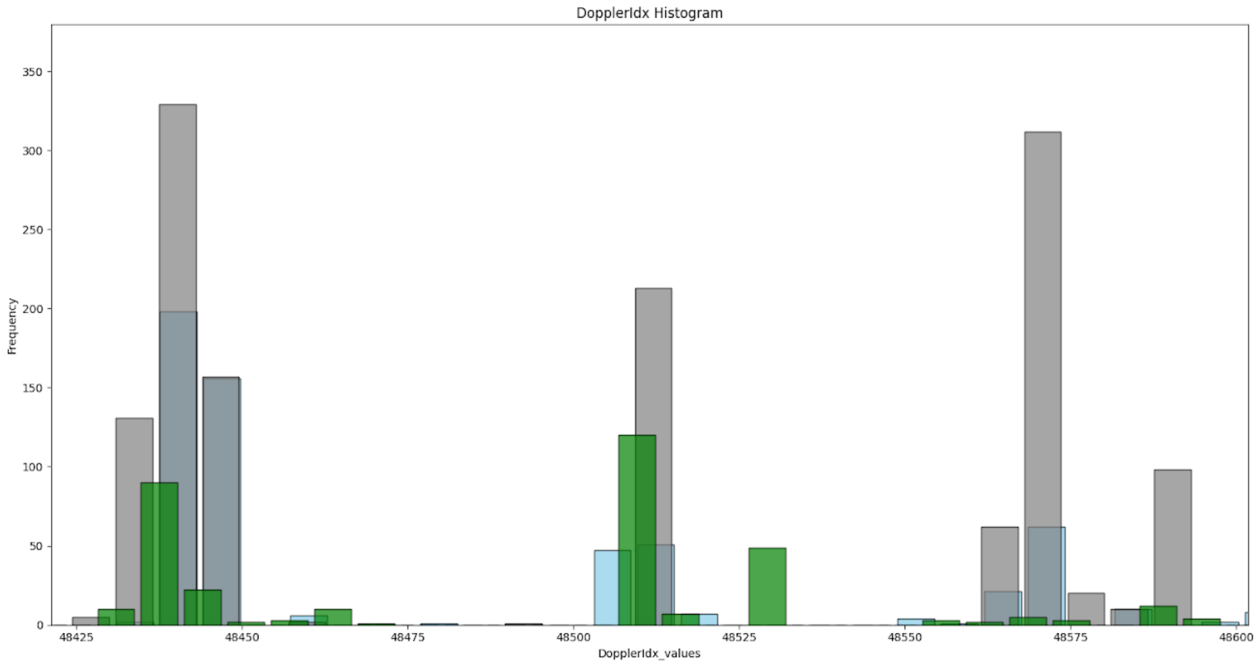

Figure 4.15 Some of the spikes of full histogram

The zoomed versions of the Histogram which expresses the spikes of the data (higher frequencies of Doppler index s) shows that in each and every spike the Fan3(green color bars) values are lower than other values.

According to the Figure 4.11, Figure 4.12, Figure 4.13 and Figure 4.14 frequencies of Green color bar values are lower than others and moreover the above graphs relieved that Grey color bars values are various than other Doppler index frequency values.

Hence the conclusion of the graph analysis, the faulty Fan3 has more movements than the new and average working Fans.

The selected scenarios for the experiment are shown as below.

1. Fan1(skyblue) - Averaged working electrical device
2. Fan2(grey) - Faulty electrical device
3. Fan3(green) - New and healthy electrical device

Please refer to the following images/graphs which is related to K-Means clustering of captured preprocessed JSON data.

The following Figure 4.16 illustrates the results of K-Means clustering [23] of captured preprocessed JSON data using FMCW radar sensor when there are no electrical appliances (no working electrical devices)

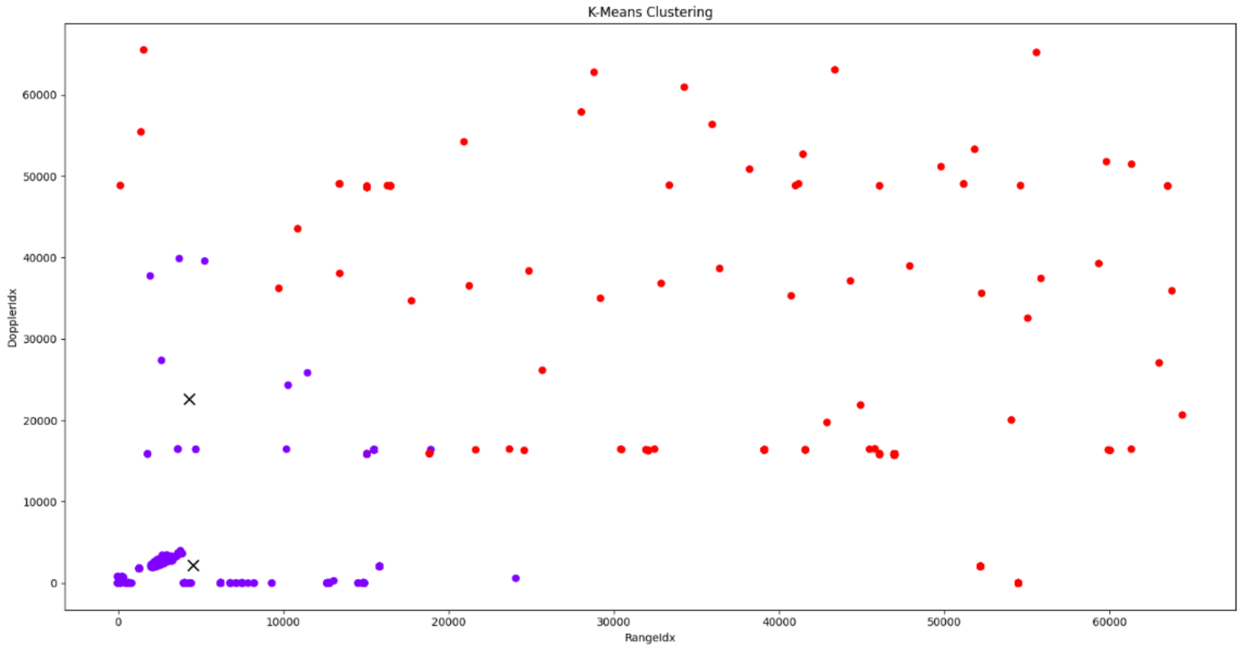

Figure 4.16 Results of K-Means clustering when there are no electrical appliances

The following Figure 4.17 illustrates the zoomed version (0 - 1000 RangeIdx values) of results of K-Means clustering of captured preprocessed JSON data using FMCW radar sensor when there are no electrical appliances (no working electrical devices)

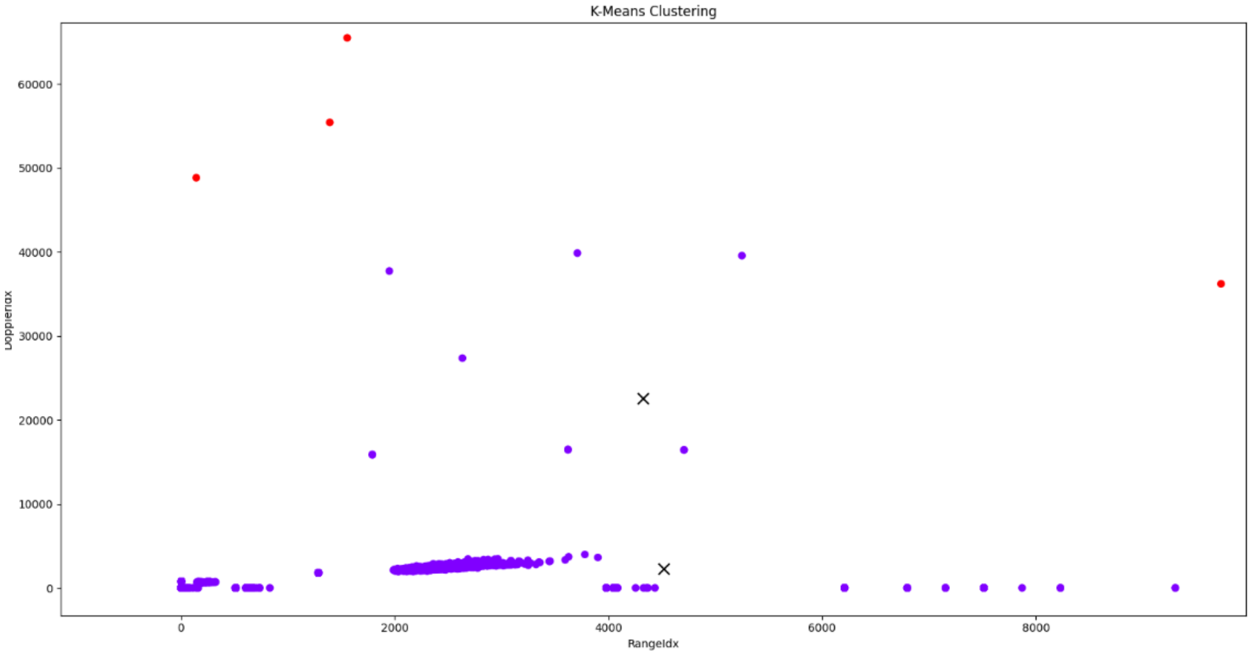

Figure 4.17 Zoomed version (0 - 1000 RangeIdx values) of results of K-Means clustering when there are no electrical appliances

Then figure 4.18 diagram illustrates the results of K-Means clustering of captured preprocessed JSON data using the FMCW mmWave radar sensor when there are some electrical appliances (working electrical devices such as ceiling fans and air conditioners within a known 1-meter distance.)

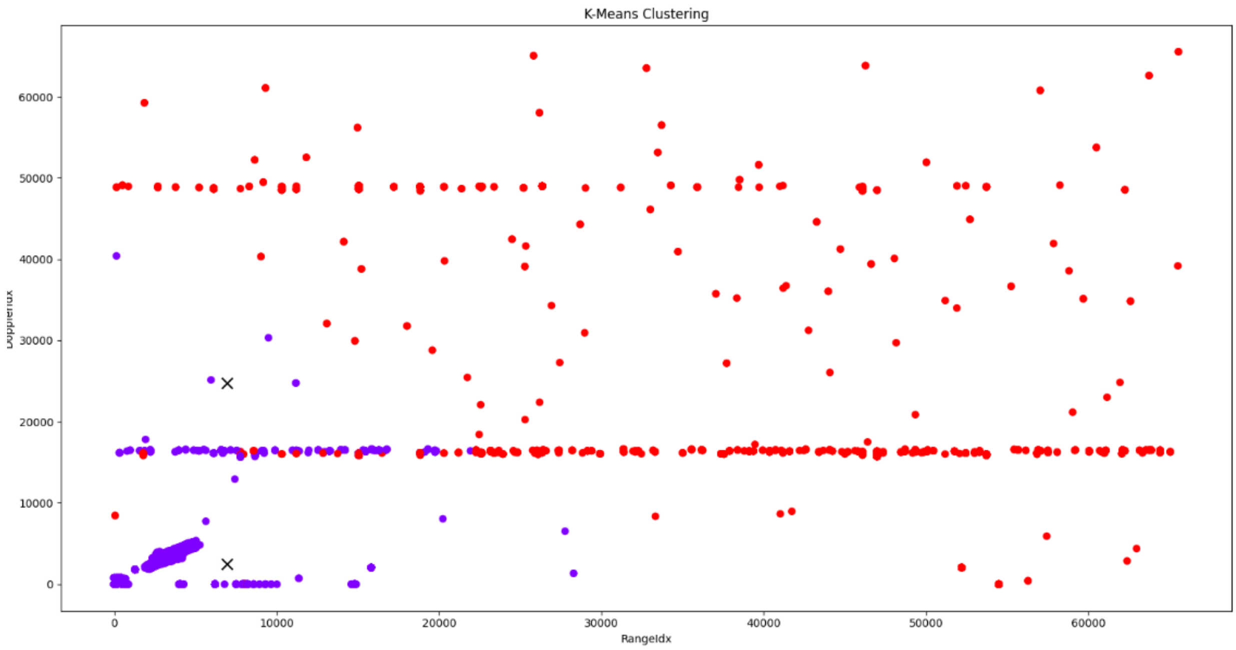

Figure 4.18 Results of K-Means clustering when there are some electrical appliances

Then figure 4.19 diagram illustrates the zoomed version (0 - 1000 RangeIdx values) of results of K-Means clustering of captured preprocessed JSON data using the FMCW mmWave radar sensor when there are some electrical appliances (working electrical devices such as ceiling fans and air conditioners within a known 1-meter distance.)

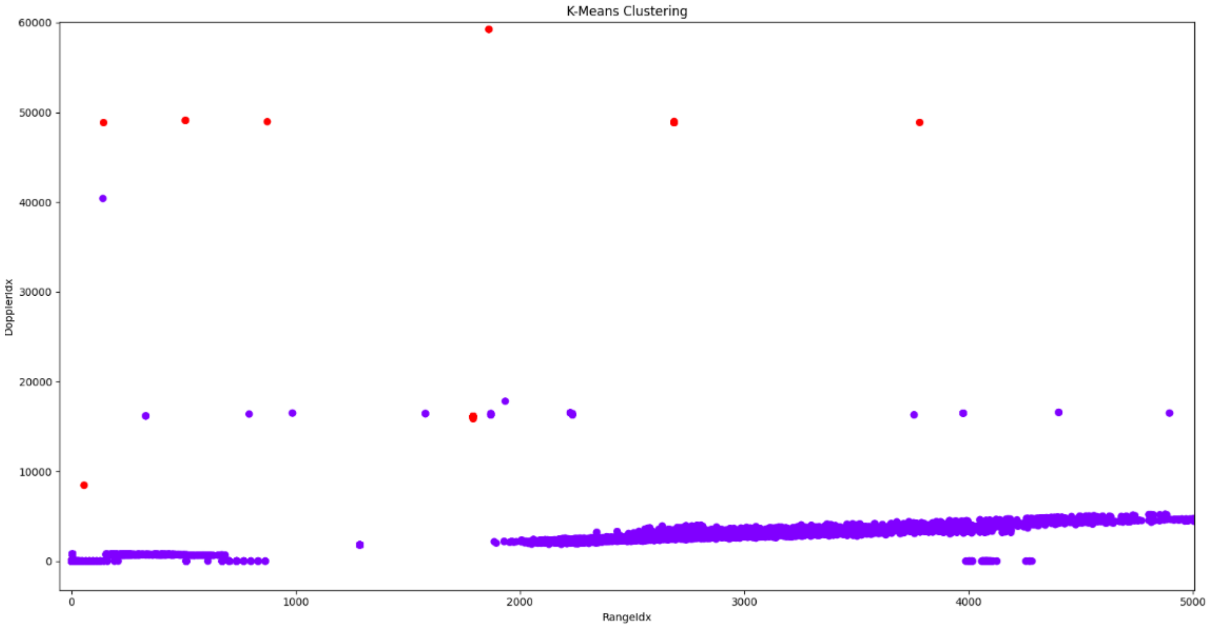

Figure 4.19 Zoomed version (0 - 1000 RangeIdx values) of results of K-Means clustering when there are some electrical appliances

According to the analysis of comparing mmWave radar signals for both of the scenarios,

- when there are some electrical appliances (working electrical devices such as ceiling fans and air conditioners) within a known 1-meter distance
- when there are no electrical appliances

There are significant differences in two clusters when detecting some working electrical appliances and when there are no electrical appliances. Basically, when the mmWave radar captures the movements and vibrations of electrical devices, we can observe that it clearly reflects the captured radar signals in the above graphs and clusters against DopplerIdx and RangeIdx values.

The results of K-Means clustering of captured preprocessed JSON data using the FMCW mmWave radar sensor of Fan1(Figure 4.19), Fan2(Figure 4.20) and Fan3(Figure 4.21) are as shown below.

By applying K-Means clustering, the research can effectively segment electrical appliance health data into distinct clusters, enabling the identification of patterns and anomalies that can aid in predictive maintenance. This allows for timely interventions to prevent breakdowns and optimize appliance performance.

While applying K-Means clustering for enhanced predictive maintenance, utilizing K-Means clustering can assist in categorizing appliances based on their health status, facilitating informed decisions on maintenance scheduling. This approach enables prioritization of maintenance tasks based on the health condition of each appliance, optimizing resource allocation and minimizing downtime.

Then figure 4.20 diagram illustrates the results of K-Means clustering of captured preprocessed JSON data of Fan1 (working electrical devices such as ceiling fans and air conditioners within a known 1-meter distance.)

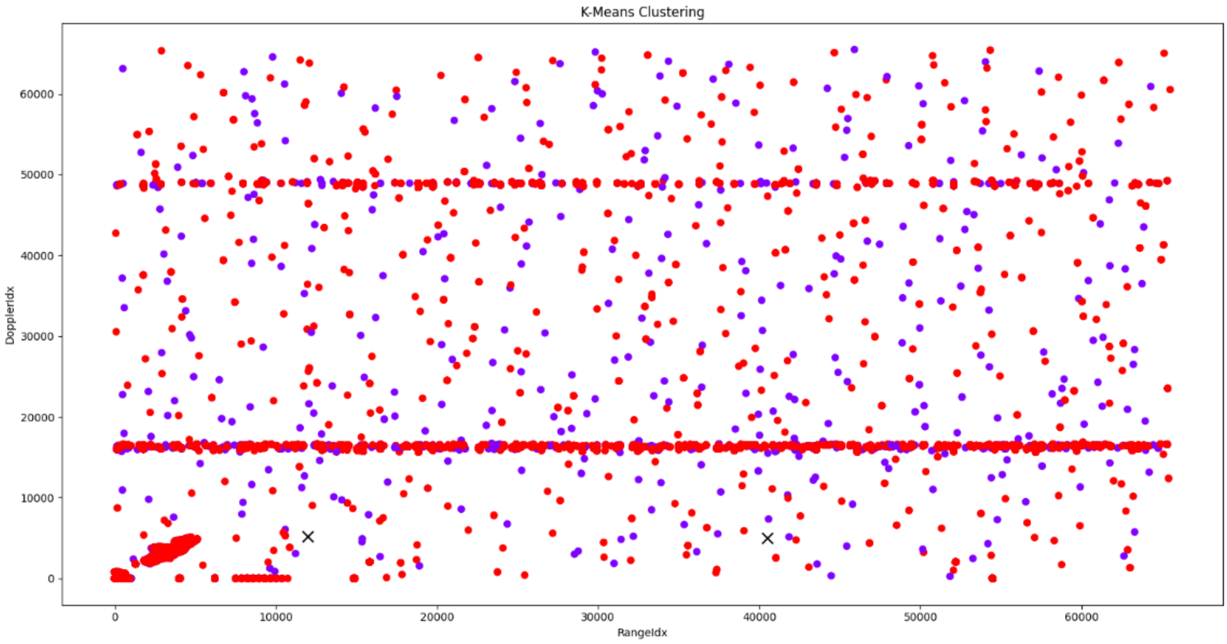

Figure 4.20 Results of K-Means clustering of captured preprocessed JSON data of Fan1

Then figure 4.21 diagram illustrates the results zoomed version (0 - 1000 RangeIdx values) of K-Means clustering of captured preprocessed JSON data of Fan1 (working electrical devices such as ceiling fans and air conditioners within a known 1-meter distance.)

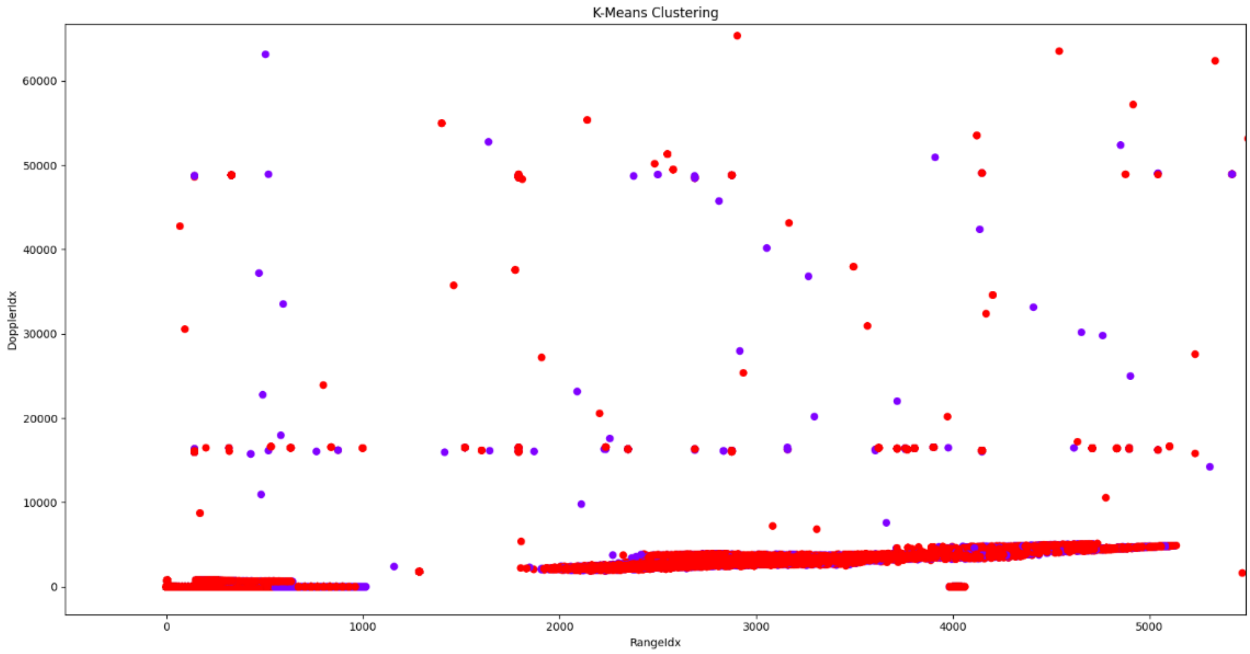

Figure 4.21 Results zoomed version (0 - 1000 RangeIdx values) of K-Means clustering of captured preprocessed JSON data of Fan1

Then figure 4.22 diagram illustrates the results of K-Means clustering of captured preprocessed JSON data of Fan2 (working electrical devices such as ceiling fans and air conditioners within a known 1-meter distance.)

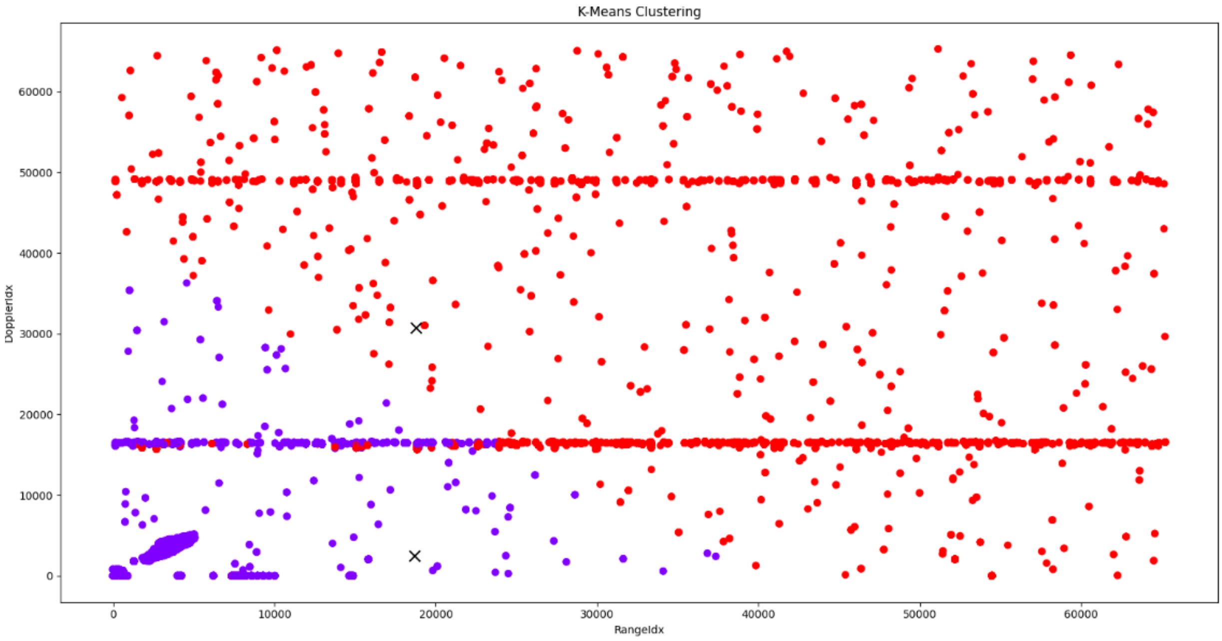

Figure 4.22 Results of K-Means clustering of captured preprocessed JSON data of Fan2

Then figure 4.23 diagram illustrates the results zoomed version (0 - 1000 RangeIdx values) of K-Means clustering of captured preprocessed JSON data of Fan2 (working electrical devices such as ceiling fans and air conditioners within a known 1-meter distance.)

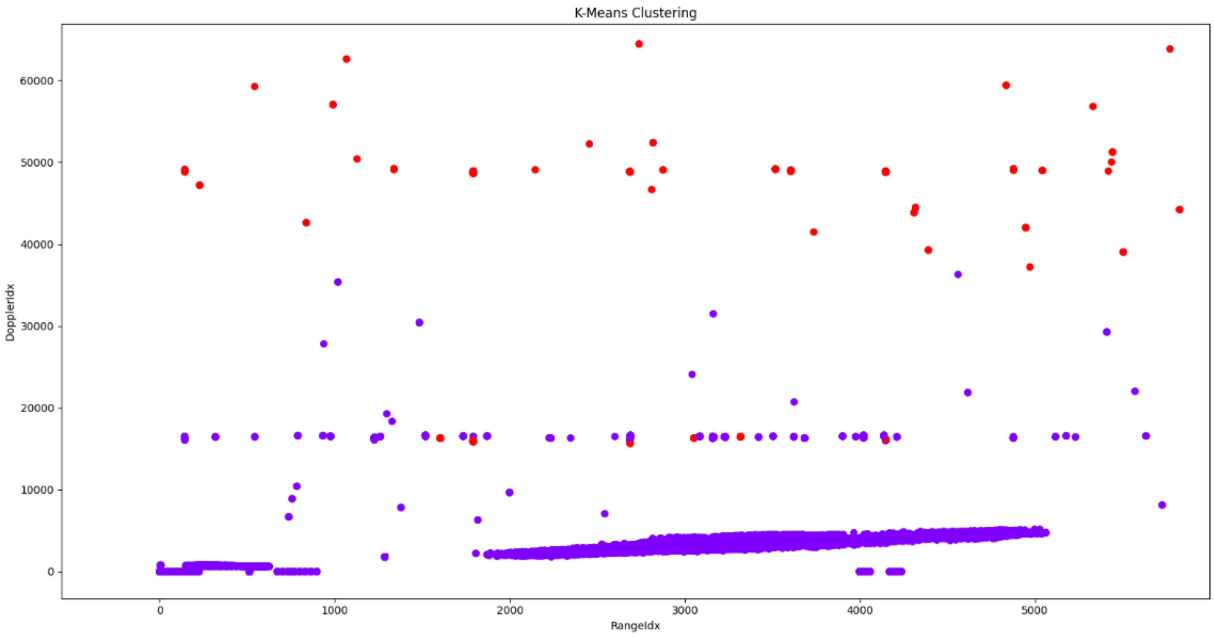

Figure 4.23 Results zoomed version (0 - 1000 RangeIdx values) of K-Means clustering of captured preprocessed JSON data of Fan2

Then figure 4.24 diagram illustrates the results of K-Means clustering of captured preprocessed JSON data of Fan3 (working electrical devices such as ceiling fans and air conditioners within a known 1-meter distance.)

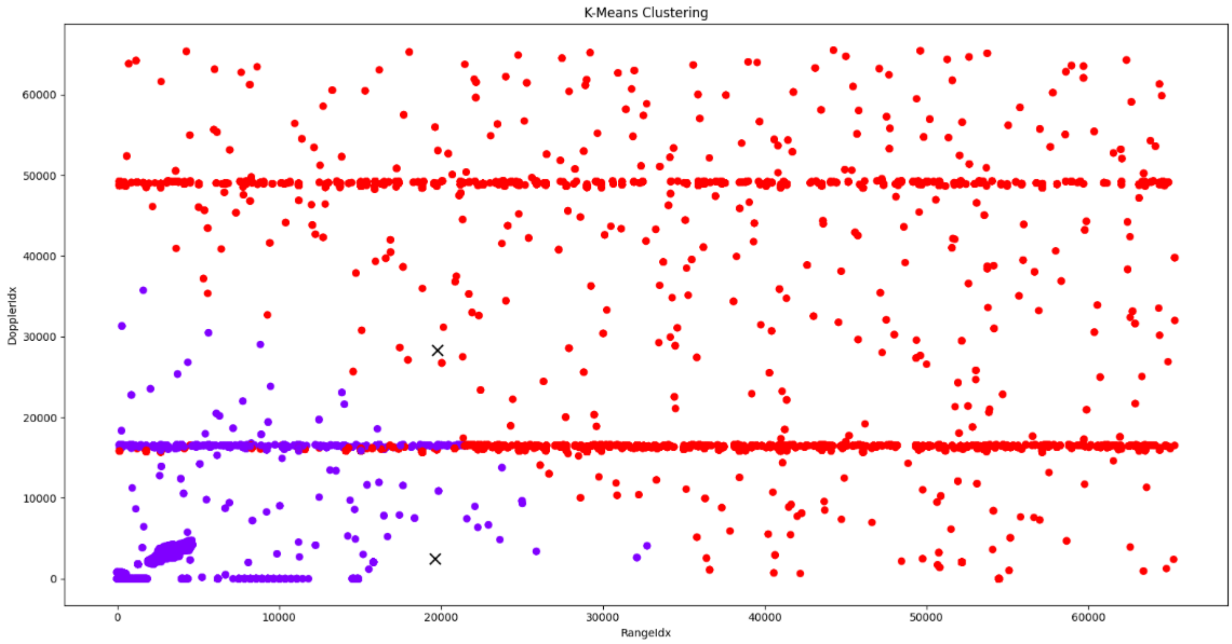

Figure 4.24 Results of K-Means clustering of captured preprocessed JSON data of Fan3

Then figure 4.25 diagram illustrates the results zoomed version (0 - 1000 RangeIdx values) of K-Means clustering of captured preprocessed JSON data of Fan3 (working electrical devices such as ceiling fans and air conditioners within a known 1-meter distance.)

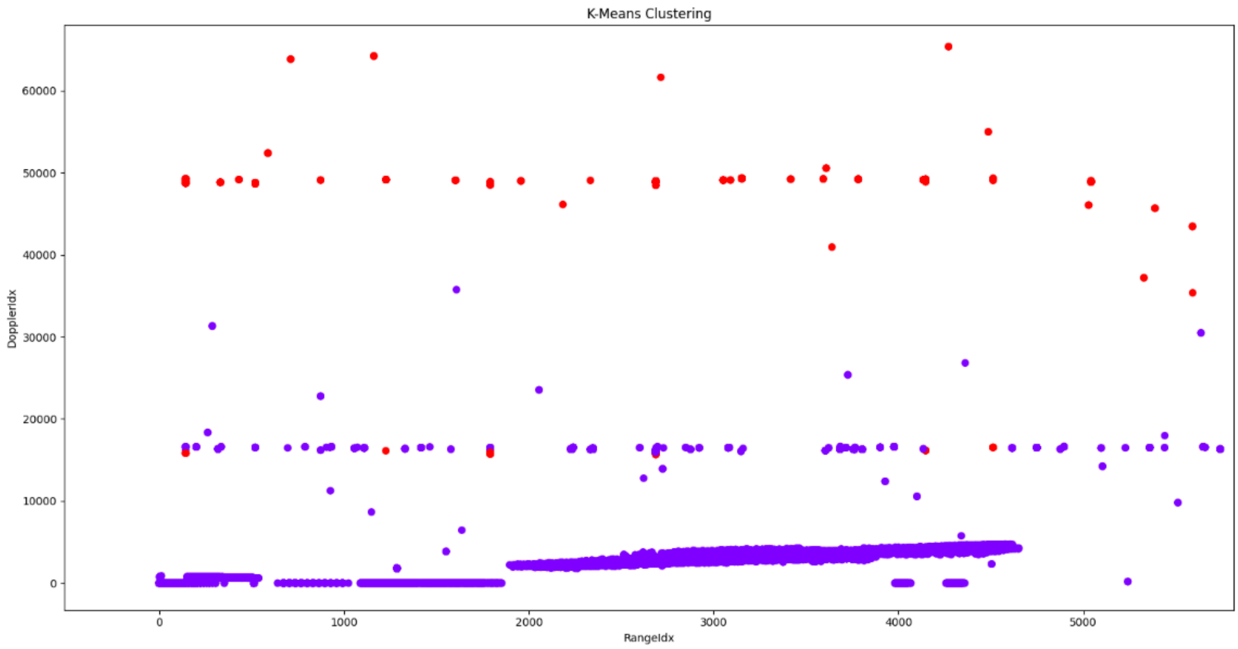

Figure 4.25 Results zoomed version (0 - 1000 RangeIdx values) of K-Means clustering of captured preprocessed JSON data of Fan3

Through the segmentation of electrical appliance health data using K-Means clustering, decision-makers can allocate resources more effectively by focusing maintenance efforts on appliances identified as high-risk or requiring immediate attention. This targeted approach to resource allocation based on cluster analysis can lead to cost savings, improved operational performance, and increased equipment reliability

K-Means clustering enables the early detection of anomalies or deviations from normal appliance health patterns. By identifying outliers or unusual behavior within clusters, decision-makers can proactively address potential issues before they escalate, leading to reduced downtime, enhanced safety, and improved overall system reliability

leveraging K-Means clustering in decision making for diagnosing electrical appliance health using mmWave Radar can result in more efficient predictive maintenance strategies, optimized resource allocation, early anomaly detection, and improved overall operational performance of electrical devices.

Based on the results of K-Means clustering of mmWave radar signals of Figure 4.23 and Figure 4.24 which are related to Fan3, there is a significant difference of DopplerIdx values' behavior in between the RangeIdx of 800 – 1000. Further the fact that the electrical device is in 1-meter distance (RangeIdx 1000) the frequencies of Doppler index values are lower than the Fan1(Figure 4.19 and Figure 4.20) and Fan2(Figure 4.21 and Figure 4.22) results of graphs.

The selected scenarios for the experiment are shown as below.

1. Fan1 - Averaged working electrical device
2. Fan2 - Faulty electrical device
3. Fan3 - New and healthy electrical device

By applying K-Means clustering to the mmWave radar data, it is possible to identify patterns and anomalies that may indicate potential maintenance needs or issues with the electrical appliances. This information can be used to inform predictive maintenance strategies and optimize resource allocation, leading to improved operational performance and reduced downtime.

CHAPTER 5 CONCLUSION AND FUTURE WORK

The study successfully demonstrated the feasibility and effectiveness of utilizing mmWave radar technology for diagnosing the health of electrical appliances. Through empirical testing and experimentation, we developed and validated signal processing techniques capable of detecting anomalies, faults, and degradation in appliance components with high accuracy and reliability. The research showcased the potential of mmWave radar-based predictive maintenance strategies in minimizing downtime, optimizing resource utilization, and extending the lifespan of electrical appliances.

Research questions & answers:

1. How can mmWave sensing technology be effectively utilized for detecting the health conditions of electrical appliances?

The mmWave Demo visualizer captures a binary set of data and we have used a python script to convert these data into readable format and plot them against various variables such as Doppler index, RangeIdx, PeakVal etc.

The analysis indicates that mmWave radar sensors can detect the presence and condition of electrical devices based on Doppler index values. Specifically, when a healthy electrical device is near the sensor, the Doppler index values, which represent frequency shifts caused by movement and vibrations, increase. This is shown in the graphs in Chapter 4, where the frequencies of the Doppler index values shift to the right. This rightward shift indicates higher Doppler index values, signifying that the radar has detected more pronounced vibrations or movements associated with the healthy functioning of the electrical device. This suggests that the device is operating normally, as abnormal conditions would likely result in different Doppler index patterns.

Further according to the graphs presented in Chapter 4, the Doppler index values, which measure the frequency shifts caused by movement and vibrations, tend to be lower and are more concentrated towards the left side of the frequency spectrum when there is a fault in an electrical device. This leftward shift indicates that the detected vibrations or movements are less pronounced compared to those of a healthy device. Lower Doppler index values suggest reduced or altered mechanical activity, which is often a sign of an underlying issue such as a mechanical fault, imbalance, or degradation in the device's performance. This pattern helps in identifying and diagnosing faults in electrical devices by comparing the Doppler index values to the expected range for normal, healthy operation.

2. What are the key parameters and metrics that can be derived from mmWave sensing data to assess the health status of electrical appliances?

Based on the results obtained with the above experiment the Doppler index value can be used as the key parameter to assess the health status of electrical appliances. The Doppler index value, derived from the Doppler effect, is a valuable parameter for assessing the health status of electrical appliances. It measures frequency shifts in mmWave radar signals caused by the movement and vibrations of mechanical parts, providing insights into their operational conditions. By establishing baseline vibration patterns and monitoring deviations over time, the Doppler index can detect mechanical issues such as imbalances, misalignments, and wear. It also helps in tracking rotational speed consistency and identifying specific fault signatures through frequency spectrum analysis. This non-contact, real-time measurement technique enables early fault detection and preventive maintenance, ensuring appliance reliability. Integrating the Doppler index with other metrics enhances comprehensive health assessment and effective maintenance strategies.

Contributions:

The primary contributions of this research include several key points. Introducing a novel approach for diagnosing electrical appliance health using mmWave radar technology, developing signal processing techniques tailored for appliance health diagnosis based on radar data, validating the accuracy and reliability of the proposed approach through empirical testing and experimentation. Once we have validated the approach using this setup, we can then proceed to analyse the captured data using dedicated machine learning algorithms. Demonstrating the practical applications and benefits of mmWave radar-based predictive maintenance strategies in real-world scenarios.

Limitations:

While the study achieved significant milestones, several limitations should be acknowledged such as the research focused primarily on a limited set of electrical appliances and scenarios, warranting further investigation across diverse applications and environments. Further the performance of the proposed approach may be influenced by factors such as sensor placement, environmental conditions, and the complexity of appliance systems. The study relied on simulated faults and controlled experiments, which may not fully capture the complexity and variability of real-world scenarios.

Future Directions:

Building upon the findings and lessons learned from this research, several avenues for future research can be explored such as investigating the scalability and adaptability of mmWave radar-based diagnostic techniques for large-scale deployment in residential and industrial settings, Exploring advanced signal processing algorithms and machine learning techniques to enhance the predictive capabilities and robustness of appliance health diagnosis, Conducting longitudinal studies and field trials to assess the long-term performance and efficacy of mmWave radar-based predictive maintenance strategies, Collaborating with industry partners to integrate mmWave radar technology into existing maintenance workflows and develop practical solutions for real-world applications are key areas that we can focus in future.

In conclusion, the research on diagnosing electrical appliance health using mmWave radar technology has laid a solid foundation for further advancements in predictive maintenance practices. By addressing the identified limitations and pursuing future research directions, we can continue to innovate and drive positive outcomes in the field of appliance health management and reliability engineering.

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Appendix A

Appendix A shows a simplified example code snippet to illustrate how we can start parsing raw data in TLV format using Python:

```
def parse_tlv_data(raw_data):
    tlv_type = raw_data[0]
    tlv_length = raw_data[1]
    tlv_value = raw_data[2:2+tlv_length]
    return tlv_type, tlv_length, tlv_value
# Read raw byte stream data
raw_data = b'\x01\x04\x12ABCD'
# Parse TLV data
tlv_type, tlv_length, tlv_value = parse_tlv_data(raw_data)
print(f"Type: {tlv_type}, Length: {tlv_length}, Value: {tlv_value}")
```

Appendix B

Appendix B shows the parseTLVmod.py python script which is used to convert binary format data into TLV format.

```
import json
import struct
import sys

def tlvHeaderDecode(data):
    tlvType, tlvLength = struct.unpack('2I', data)
    return tlvType, tlvLength

def parseDetectedObjects(data, tlvLength):
    numDetectedObj, xyzQFormat = struct.unpack('2H', data[:4])
    print("\tDetect Obj:\t%d " % (numDetectedObj))
    packet_dict["Detected Obj"] = numDetectedObj
    for i in range(numDetectedObj):
        print("\tObjId:\t%d " % (i))
        obj_dict["ObjId"] = i
        rangeIdx, dopplerIdx, peakVal, x, y, z = struct.unpack('3H3h', data[4
+ 12 * i:4 + 12 * i + 12])
        print("\t\tDopplerIdx:\t%d " % (dopplerIdx))
        print("\t\tRangeIdx:\t%d " % (rangeIdx))
        print("\t\tPeakVal:\t%d " % (peakVal))
        obj_dict["DopplerIdx"] = dopplerIdx
        obj_dict["RangeIdx"] = rangeIdx
        obj_dict["PeakVal"] = peakVal
        packet_dict["obj_data"].append(obj_dict)

def tlvHeader(data):
```

```
    j = 0
    while data:
        headerLength = 36
        try:
            magic, version, length, platform, frameNum, cpuCycles, numObj,
numTLVs = struct.unpack('Q7I',

                      data[:headerLength])
        except:
            print("Improper TLV structure found: ")
            break
        print("Packet ID:\t%d " % (frameNum))
        print("Version:\t%x " % (version))
        print("TLV:\t\t%d " % (numTLVs))
        print("Detect Obj:\t%d " % (numObj))
        print("Platform:\t%X " % (platform))
        packet_dict["Packet ID"] = frameNum
        packet_dict["Version"] = version
        packet_dict["TLV"] = numTLVs
        packet_dict["Detect Obj"] = numObj
        packet_dict["Platform"] = platform

        if version > 0x01000005:
            subFrameNum = struct.unpack('I', data[36:40])[0]
            headerLength = 40
            # print("Subframe:\t%d " % (subFrameNum))
            packet_dict["Subframe"] = subFrameNum
            pendingBytes = length - headerLength
            data = data[headerLength:]
            for i in range(numTLVs):
                tlvType, tlvLength = tlvHeaderDecode(data[:8])
                data = data[8:]
                if tlvType == 1:
                    parseDetectedObjects(data, tlvLength)
                    result_dict["PacketIDs"].append(packet_dict)
                    j += 1
                    if j == 10:
                        create_json_file(result_dict,
'./2024_02_10/output_json_data/output_noACnoFan.json')
                        return
                else:
                    print("Unidentified tlv type %d" % (tlvType))
                data = data[tlvLength:]
                pendingBytes -= (8 + tlvLength)
            data = data[pendingBytes:]
            yield length, frameNum

def create_json_file(data, file_name):
    with open(file_name, 'w') as file:
        json.dump(data, file)

result_dict = {"PacketIDs": []}
packet_dict = {"obj_data": []}
```

```python
obj_dict = {}

if __name__ == "__main__":
    if len(sys.argv) != 2:
        print("Usage: parseTLV.py inputFile.bin")
        sys.exit()

    fileName = sys.argv[1]
    rawDataFile = open(fileName, "rb")
    rawData = rawDataFile.read()
    rawDataFile.close()
    magic = b'\x02\x01\x04\x03\x06\x05\x08\x07'
    offset = rawData.find(magic)
    rawData = rawData[offset:]
    for length, frameNum in tlvHeader(rawData):
        print
```

Appendix C

Appendix C shows the sample result which is obtained by executing the script shown in Appendix B.

```
Packet ID:  7924
Version:    3020004
TLV:        4
Detect Obj: 7
Platform:   A1843
    Detect Obj: 8671
    ObjId:  0
        DopplerIdx: 16496
        RangeIdx:   985
        PeakVal:    0
    ObjId:  1
        DopplerIdx: 0
        RangeIdx:   0
        PeakVal:    46975
    ObjId:  2
        DopplerIdx: 16160
        RangeIdx:   18830
        PeakVal:    35902
    ObjId:  3
        DopplerIdx: 0
        RangeIdx:   0
        PeakVal:    26362
………
……..
……..
```

Appendix D

Appendix D shows the python script to convert the TLV format to JSON format

```python
import json

# Open the file for reading
file_path = "./../2024_02_10/output_txt_data/sample_output_withACwithFan.txt"
writeJSONFile =
'./../2024_02_10/output_json_data/sample_output_withACwithFan.json'

file = open(file_path, mode="r")
content = file.read()

file.close()

# Initialize an empty dictionary
result_dict = {"obj_data": []}
obj_dict = {}

# Process the data
lines = content.strip().split("\n")
for line in lines:
    parts = line.split(":")
    # print(parts)
    if len(parts) == 2 and (
            "ObjId" in parts[0] or "DopplerIdx" in parts[0] or "RangeIdx" in
parts[0] or "PeakVal" in parts[0]):
        sub_key, sub_value = parts[0].strip(), parts[1].strip()
        obj_dict[sub_key] = sub_value
        if "PeakVal" in parts[0] and len(result_dict["obj_data"]) <= 200000:
            result_dict["obj_data"].append(obj_dict)
            obj_dict = {}
            print(len(result_dict["obj_data"]))
    elif len(parts) == 2:
        key, value = parts[0].strip(), parts[1].strip()
        result_dict[key] = value

def create_json_file(data, file_name):
    with open(file_name, 'w') as file:
        json.dump(data, file)

# Convert to JSON
json_data = json.dumps(result_dict, indent=4)

# Example usage
create_json_file(result_dict, writeJSONFile)
```

Appendix E

Appendix E shows the result of converting TLV format into JSON format by executing script shown in Appendix D.


```
{
    "Packet ID": "7924",
    "Version": "3020004",
    "TLV": "4",
    "Detect Obj": "8671",
    "Platform": "A1843",
    "obj_data": [
        {
            "ObjId": "0",
            "DopplerIdx": "16496",
            "RangeIdx": "985",
            "PeakVal": "0"
        },
        {
            "ObjId": "1",
            "DopplerIdx": "0",
            "RangeIdx": "0",
            "PeakVal": "46975"
        },
        {
            "ObjId": "2",
            "DopplerIdx": "16160",
            "RangeIdx": "18830",
            "PeakVal": "35902"
        },
        {
            "ObjId": "3",
            "DopplerIdx": "0",
            "RangeIdx": "0",
            "PeakVal": "26362"
        },
        {
            "ObjId": "4",
            "DopplerIdx": "16409",
            "RangeIdx": "38799",
            "PeakVal": "0"
        },
......
......
......
}
```

Appendix F

Appendix F shows the python script to plot histogram using the generated JSON format.

```
import json
import matplotlib.pyplot as plt
import pandas as pd

with open('./../2024_03_02/output_json_data/output_Fan1d.json', 'r') as
json_file:
    data1 = json.load(json_file)

with open('./../2024_03_02/output_json_data/output_Fan2d.json', 'r') as
json_file:
    data2 = json.load(json_file)

with open('./../2024_03_02/output_json_data/output_Fan3d.json', 'r') as
json_file:
    data3 = json.load(json_file)

# Extract data from the JSON
obj_data1 = data1["obj_data"]
obj_data2 = data2["obj_data"]
obj_data3 = data3["obj_data"]

DopplerIdxs1 = [entry["DopplerIdx"] for entry in obj_data1]
DopplerIdxs2 = [entry["DopplerIdx"] for entry in obj_data2]
DopplerIdxs3 = [entry["DopplerIdx"] for entry in obj_data3]

DopplerIdx1 = list(map(int, DopplerIdxs1))
DopplerIdx2 = list(map(int, DopplerIdxs2))
DopplerIdx3 = list(map(int, DopplerIdxs3))

df1 = pd.DataFrame(data1["obj_data"])
df1 = pd.DataFrame(obj_data1)
df1.sort_values('DopplerIdx', inplace=True)

df2 = pd.DataFrame(data2["obj_data"])
df2 = pd.DataFrame(obj_data2)
df2.sort_values('DopplerIdx', inplace=True)

df3 = pd.DataFrame(data3["obj_data"])
df3 = pd.DataFrame(obj_data3)
df3.sort_values('RangeIdx', inplace=True)

plt.hist(DopplerIdx1, bins=10000, color='skyblue', edgecolor='black',
alpha=0.7, rwidth=0.85)
plt.hist(DopplerIdx2, bins=10000, color='grey', edgecolor='black', alpha=0.7,
rwidth=0.85)
plt.hist(DopplerIdx3, bins=10000, color='green', edgecolor='black', alpha=0.7,
rwidth=0.85)
```

```python
# Adding labels and title
plt.xlabel('DopplerIdx_values')
plt.ylabel('Frequency')
plt.title('DopplerIdx Histogram')

# Display the plot
plt.show()
```