

GROUP 3

**DATA
PREPROCESSING
OF LIDAR USING
FPGA**

GUIDED BY JAGADEESH KUMAR P

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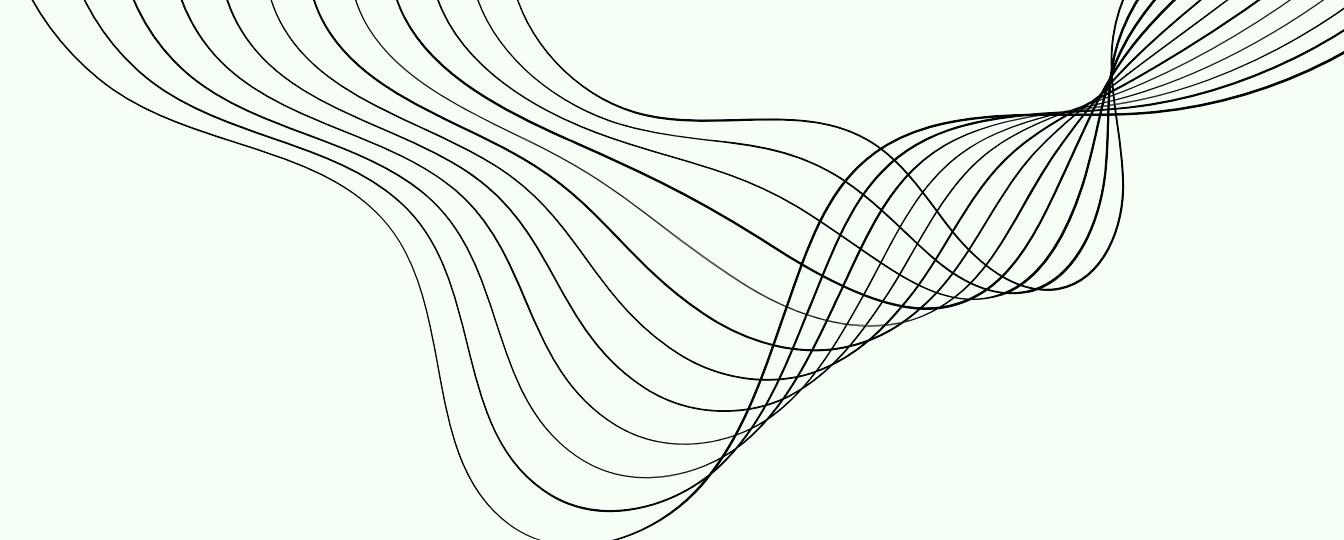
OBJECTIVE

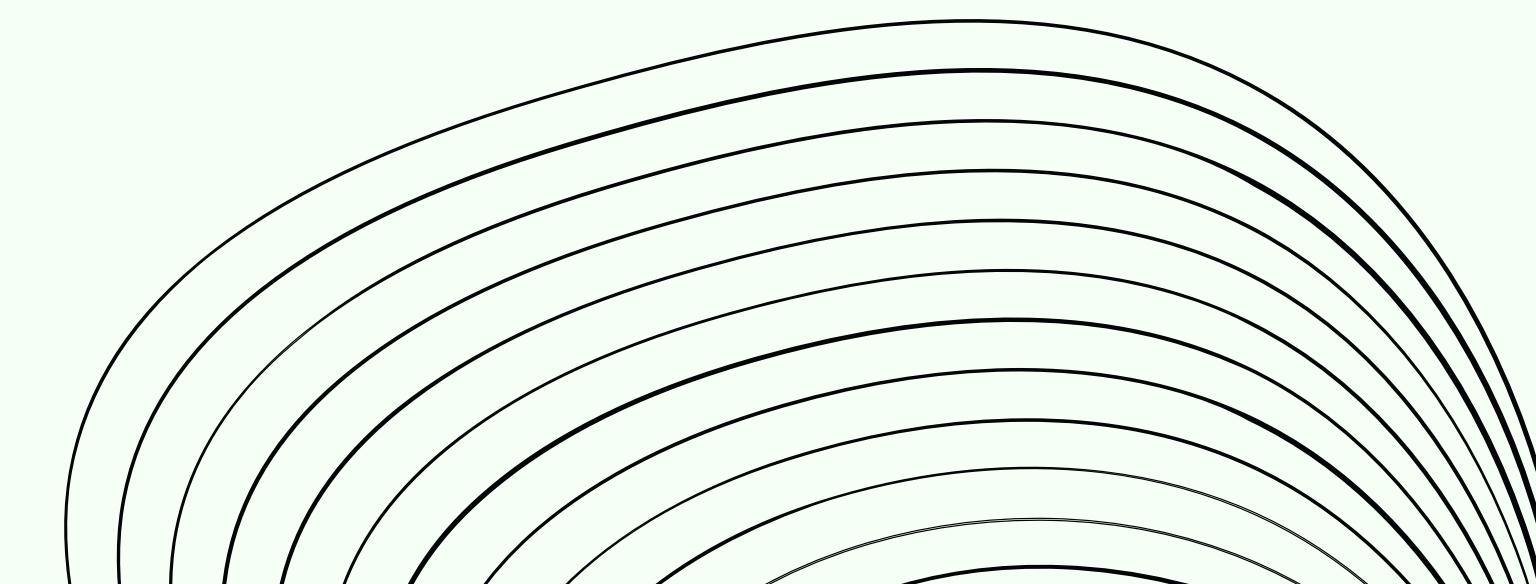
The objective of preprocessing LiDAR data using FPGA is to enhance efficiency by offloading computational tasks to hardware acceleration, thereby reducing processing time. Additionally, it aims to optimize data quality through real-time noise reduction and filtering before further analysis or storage.

SCOPE

- Point Cloud Generation
- Object Recognition and Classification
- Mapping and Surveying
- Autonomous Systems
- Environmental Monitoring

RELEVANCE



- Speed and efficiency
 - Customization and optimization
 - Power efficiency
 - Integration and scalability
 - Real time decision making
- 

WHY FPGA FOR LIDAR DATA PROCESSING?

- Parallel Processing Capability
- Real-Time or Near-Real-Time Processing
- Customization and Flexibility
- Power Efficiency
- Scalability
- Low Latency
- Reduced Dependence on CPU

LITERATURE REVIEW

SL NO	RESEARCH PAPER	YEAR	AUTHORS	FINDINGS OF THE STUDY
1	"Noise Reduction of LiDAR Signal via Local Mean Decomposition Combined With Improved Thresholding Method"	2020	Luyao Zhang, Jianhuah Chang, Hongxu Li, Zhen Xing Liu, Shuyi Zhang, Rengxiang Mao	<ul style="list-style-type: none"> • LiDAR data is often disrupted by various noise like dark current, quantum noise, amplifier noise, and background noise. • LMD dissects the complex LiDAR signal into intrinsic mode functions, enabling a detailed signal analysis. • ITM effectively eliminates noise components, thereby enhancing signal fidelity.
2	"Denoising of a Multi-Station Point Cloud and 3D Modeling Accuracy for Substation Equipment Based on Statistical Outlier Removal"	2020	Jianlong Guo, Weixia Feng, Tengfei Hao, Peng Wang, Shuang Xia, Huben Mao	<ul style="list-style-type: none"> • Create a 3D model of a substation by using laser scanning to capture information about its equipment from different angles by using a method called Statistical Outlier Removal (SOR) identify and remove the unwanted noise points. • They're specifically looking at two things: <ol style="list-style-type: none"> 1. The standard deviation of the method (how much it allows for variation). 2. The number of points it considers when figuring out what to keep and what to remove.
3	"Real-Time Driving Scene Understanding via Efficient 3-D LIDAR Processing"	2022	Wonje Jang, Minseong Park, Euntai Kim	<ul style="list-style-type: none"> • The method uses a point cloud classification network (PCCN) that combines handcrafted features and a shallow network to extract both global and local information of a given point cloud. • The PCCN is designed to classify the raw point cloud data into four classes: structured landmarks, moving objects, static obstacles, and roads. • PCCN is aimed at minimizing the performance degradation of full deep learning networks while requiring significantly less computation time than deep networks.

SL NO	RESEARCH PAPER	YEAR	AUTHORS	FINDINGS OF THE STUDY
4.	" A Survey of Automotive Radar and Lidar Signal Processing and Architectures"	2022	Luigi Giuffrida, Guido Masera, Maurizio Martina	<ul style="list-style-type: none"> The overall idea is to provide a comprehensive survey of the latest developments in on-vehicle sensing systems specifically automotive Radar and LiDAR It is suggested that a combination of radar and lidar technologies ,along with other sensors can provide a more comprehensive and reliable sensing system for ADASs and autonomous driving. It aims to provide a balanced view of radar and lidar technologies without explicitly favoring one over the other
5.	"Environmental Detection for Autonomous Vehicles Based on Multi-View Image and 3D LiDAR Point Cloud Map"	2021	Yu-Cheng Fan, Guo-Han Lin, You-Sheng Xiao, Wei-Zhe Yan	<ul style="list-style-type: none"> In this paper, 3D point cloud and depth map fusion system for 3D environment detection is proposed. This algorithm uses the depth map generated by virtual perspective mapping technology to assist LiDAR point cloud map information matching, and distinguishes objects according to distance and color to facilitate observation. The method solves the problems of sparse point cloud information of distant objects, reflections caused by the material of cars, and light penetration caused by glass, so that the point cloud map information can be more accurate.
6.	"Automatic Label Injection Into Local Infrastructure LiDAR Point Cloud for Training Data Set Generation"	2022	Zsolt Vincze, Andras Rovid, Viktor Tihanyi	<ul style="list-style-type: none"> The representation of objects in LiDAR point clouds is changed as the height of the mounting position of sensor devices gets increased. Most of the available open datasets for training machine learning based object detectors are generated with vehicle top mounted sensors, thus the detectors trained on such datasets perform weaker when the sensor is observing the scene from a significantly higher viewpoint.

SL NO	RESEARCH PAPER	YEAR	AUTHORS	FINDINGS OF THE STUDY
				<ul style="list-style-type: none"> In this paper a novel Automatic Label Injection method is proposed to label the objects in the point cloud of the high-mounted infrastructure LiDAR sensor based on the output of a well performing “trainer” detector deployed at optimal height while considering the uncertainties caused by various factors described in detail throughout the paper.
7.	“Extraction of Vehicle Groups in Airborne Lidar Point Clouds With Two-Level Point Processes”	2015 09	Attila Borcs, Csaba Benedek	<ul style="list-style-type: none"> A new object-based hierarchical model for the joint probabilistic extraction of vehicles and groups of corresponding vehicles-called traffic segments-in airborne light detection and ranging (Lidar) point clouds collected from dense urban areas. First, the 3-D point set is classified into terrain, vehicle, roof, vegetation, and clutter classes. Then, the points with the corresponding class labels and echo strength (i.e., intensity) values are projected to the ground.
8.	“Stereo-Camera-Based Urban Environment Perception Using Occupancy Grid and Object Tracking”	2015	Thien-Nghia Nguyen, Bernd Michaelis, Member, Ayoub AlHamadi, Michael Tornow, Marc-Michael Meinecke	<ul style="list-style-type: none"> In this paper it deals with environment perception for automobile applications. Environment perception comprises measuring the surrounding field with onboard sensors such as cameras, radar, lidars, etc., and signal processing to extract relevant information for the planned safety or assistance function.

SL NO	RESEARCH PAPER	YEAR	AUTHORS	FINDINGS OF THE STUDY
9.	“A Robust Signal Preprocessing Chain for Small-Footprint Waveform LiDAR”	2017	Jiaying Wu, J. A. N. van Aardt, Joseph (Joe) McGlinchy, Gregory P. Asner	<ul style="list-style-type: none"> • The raw incoming LiDAR waveform exhibits a stretched, misaligned, and relatively distorted character or the signal is smeared and the effective temporal resolution decreases, which is attributed to a fixed time span allocated for detection, the sensor's variable outgoing pulse signal, the receiver impulse response impacts, and system noise. • In this paper, we present a robust signal preprocessing chain for waveform LiDAR calibration, which includes noise reduction, deconvolution, waveform registration, and angular rectification.
10.	“Point Cloud Preprocessing on 3D LiDAR data for Unmanned Surface Vehicle in Marine Environment”	2018	Xianzhi Qi, Wenxing Fu, Pei An, Bingli Wu, Jie Ma	<ul style="list-style-type: none"> • Point cloud preprocessing is challenging task in the marine environment, for it is difficult to filter out non-obstacle points while avoiding damage to the obstacle completeness. In this paper, we a novel data preprocessing method on 3D LiDAR data for the unmanned surface vehicle in the marine environment. • It consists of two tasks: outlier removal and wake filtering.

INTRODUCTION

- Raw LiDAR data can be noisy due to factors like atmospheric conditions, sensor inaccuracies, and unwanted reflections.
- Preprocessing includes filtering, segmentation, and feature extraction.
- The refined the data is suitable for terrain modeling, object recognition, and autonomous navigation.

SYSTEM OVERVIEW

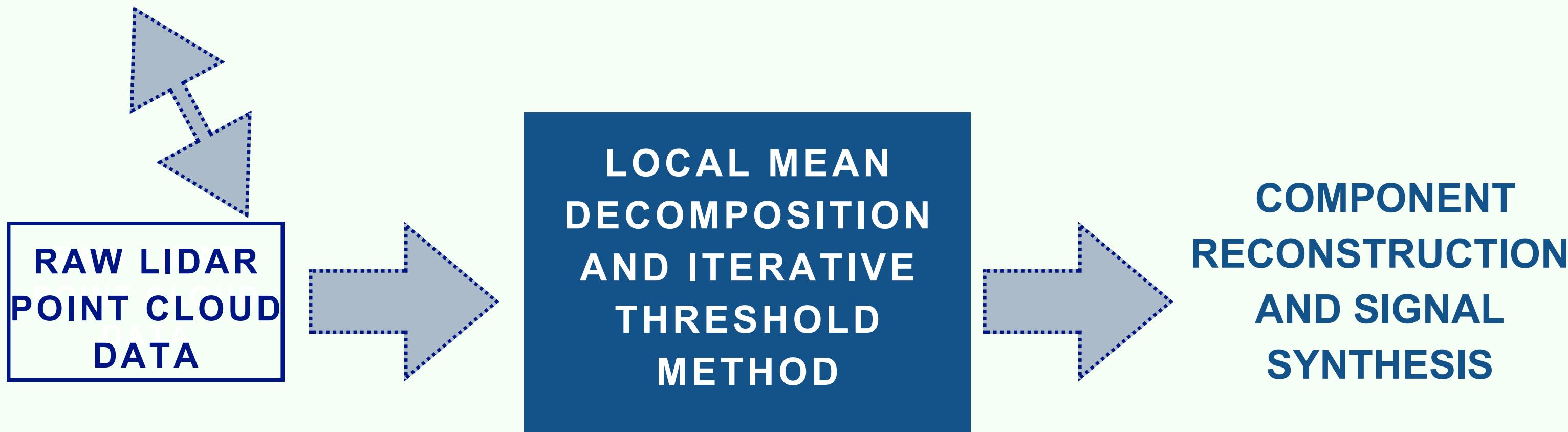
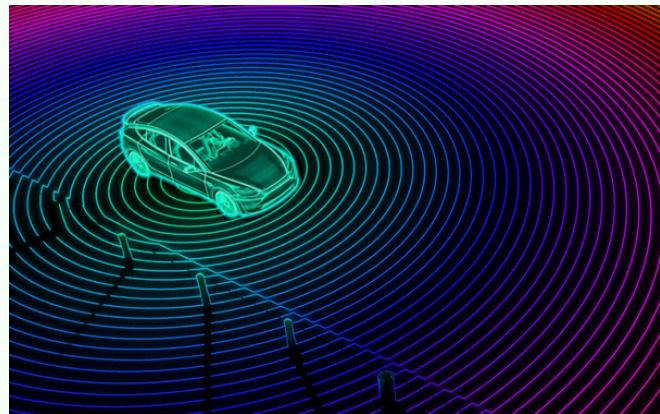


Figure 1: Project overview : Integration of LMD-ITM filtering methods to achieve preprocessed lidar data for Object tracking and Visualisation

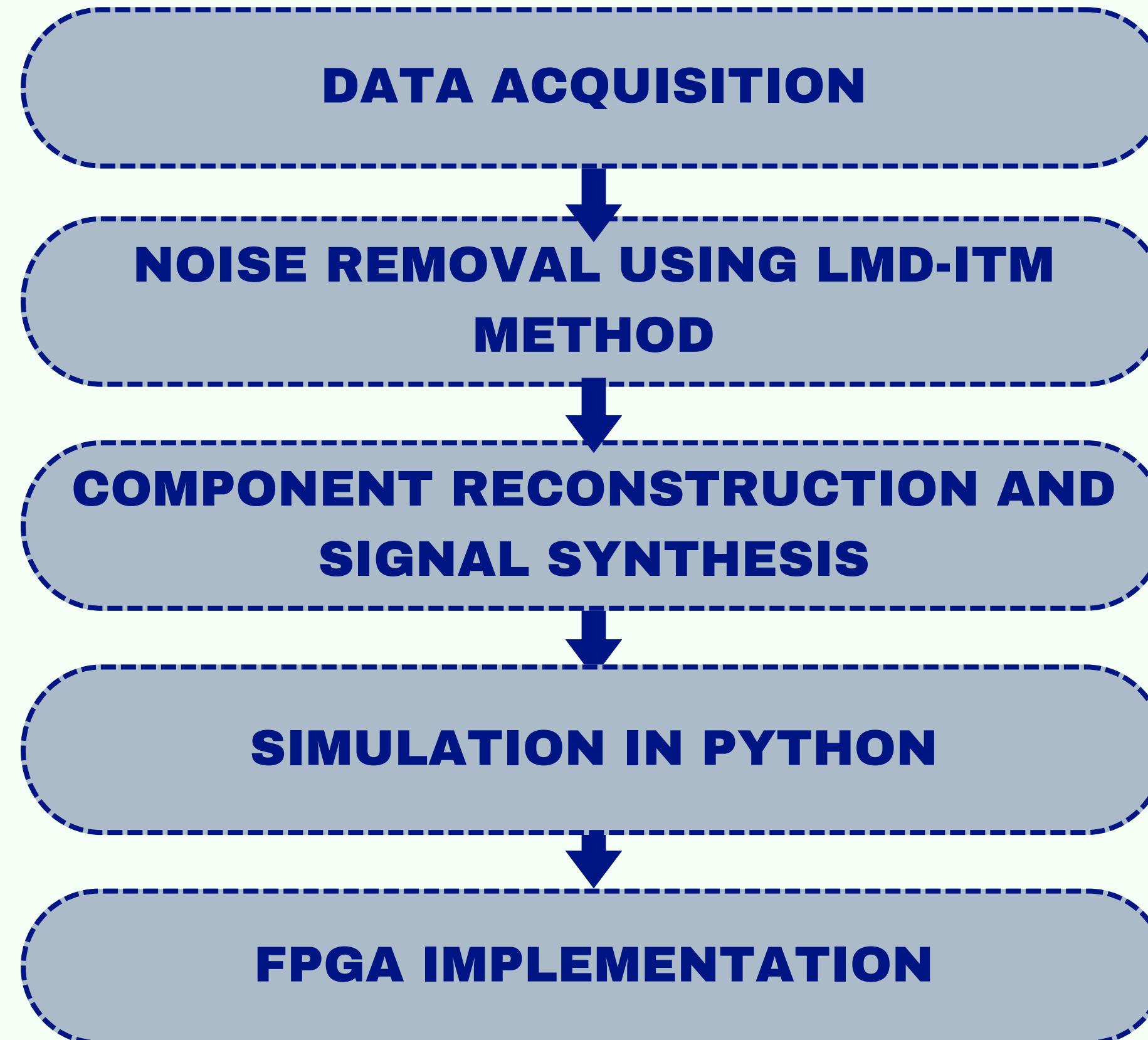
LIDAR DATA : Lidar Sensor provides essential information for object tracking

FILTERING METHODS : Removal of noise from the raw lidar data using Local mean decomposition and Iterative Threshold Method

NOISE REMOVAL

- Statistical Methods: Techniques like median filtering, Gaussian smoothing, or wavelet-based denoising are applied to further clean the data.
- Outlier Detection and Removal: Identifies and removes outlier points that don't fit the general pattern of the data.
- The FPGA processes the filtered data, applying noise removal algorithms to produce a clean point cloud.

WORKFLOW OF THE PROJECT



DIFFERENT METHODS USED

DATA ACQUISITION

LiDAR (Light Detection and Ranging) data is used to generate detailed 3D information about environments.

It is often represented as point clouds, with each point containing specific data such as coordinates, intensity, etc.

Content of LiDAR Dataset

- X, Y, Z Coordinates: These represent the 3D position of each point in space.
- Intensity: A measure of the reflected signal strength for each point.
- Return Number: Indicates the order of the return for a specific pulse.
- Number of Returns: The total number of returns for a specific pulse.
- Scan Angle: The angle at which the LiDAR pulse was emitted relative to the scanner.
- Time: Timestamp indicating when the point was recorded.

Sample LiDAR Data Structure in .txt Form

The .txt file typically contains a list of points with relevant data, separated by spaces or commas. Here's a simple example:

#	X	Y	Z	Intensity	Return_Number	Number_of_Returns	Scan_Angle
-123.456	789.123	12.345	150	1	3	-10.5	1625040000.123
-123.457	789.124	12.346	145	2	3	-10.6	1625040000.124
-123.458	789.125	12.347	140	1	2	-10.7	1625040000.125
-123.459	789.126	12.348	155	1	1	-10.8	1625040000.126

FIG 2: FORMAT OF LIDAR DATA

NOISE REMOVAL USING LMD

- The main cause of noise pollution - dark current noise, signal-induced quantum noise, amplifier noise, and background noise
- These noises do not interfere with each other, and the total noise can be obtained by summing the independent random variables.
- Various methods like the moving average (MA), Kalman filtering (KF), etc has been introduced.
- The most effective method is LMD-ITM with a remarkable 15% increase in Signal-to-Noise Ratio (SNR).

Local Mean Decomposition (LMD) Process:

- LMD is a signal decomposition technique designed to break down signals into a series of product functions using iterations.
- The goal is to capture key signal components, including the envelope and frequency modulation, through a double-cycle process.

Local Mean Decomposition (LMD) Process:

- Step 1: Find the maxima and minima as the local extremes in the original signal $x(t)$.
- Step 2: Calculate the mean value m_i by two consecutive extrema n_i and n_{i+1} .
- Step 3: Generate the upper and lower envelopes by connecting the local maxima and minima, respectively.
- Step 4: Calculate the mean of the upper and lower envelopes to obtain the mean envelope m_i .

- Step 5: Compute the local mean signal a_i by averaging the upper and lower envelopes.
- Step 6: Obtain the residue $h(t)$ by subtracting the local mean signal from the original signal.
- Step 7: Repeat the above steps for the residue signal until a satisfactory decomposition is achieved.

EQUATIONS USED IN LMD-ITM METHOD

$$m_i = \frac{n_i + n_{i+1}}{2}$$

$$a_i = \frac{|n_i - n_{i+1}|}{2}$$

$$h_{11}(t) \equiv x(t) - m_{11}(t)$$

- The product function obtained is compared with energy entropy and correlation coefficient values to obtain the relevant and irrelevant components.
- The necessary components after the filtration is resampled to produce a new signal.

Implementation in Python

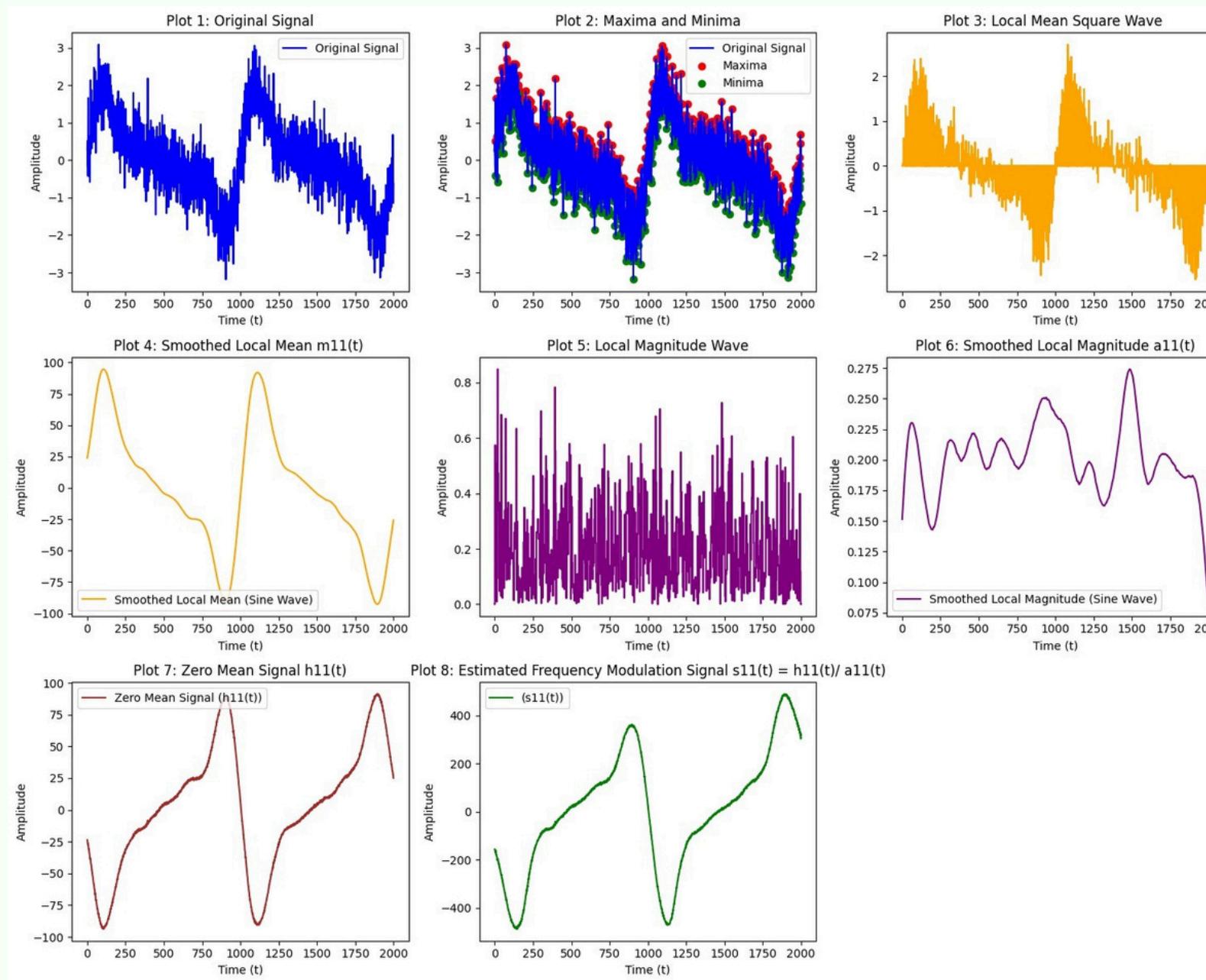


fig 3: LMD Meth

ITERATIVE THRESHOLDING METHOD (ITM)

Iterative Thresholding Method (ITM):

- It operates by selectively retaining or suppressing signal components based on thresholding principles.
- Adaptive thresholding method is used here.

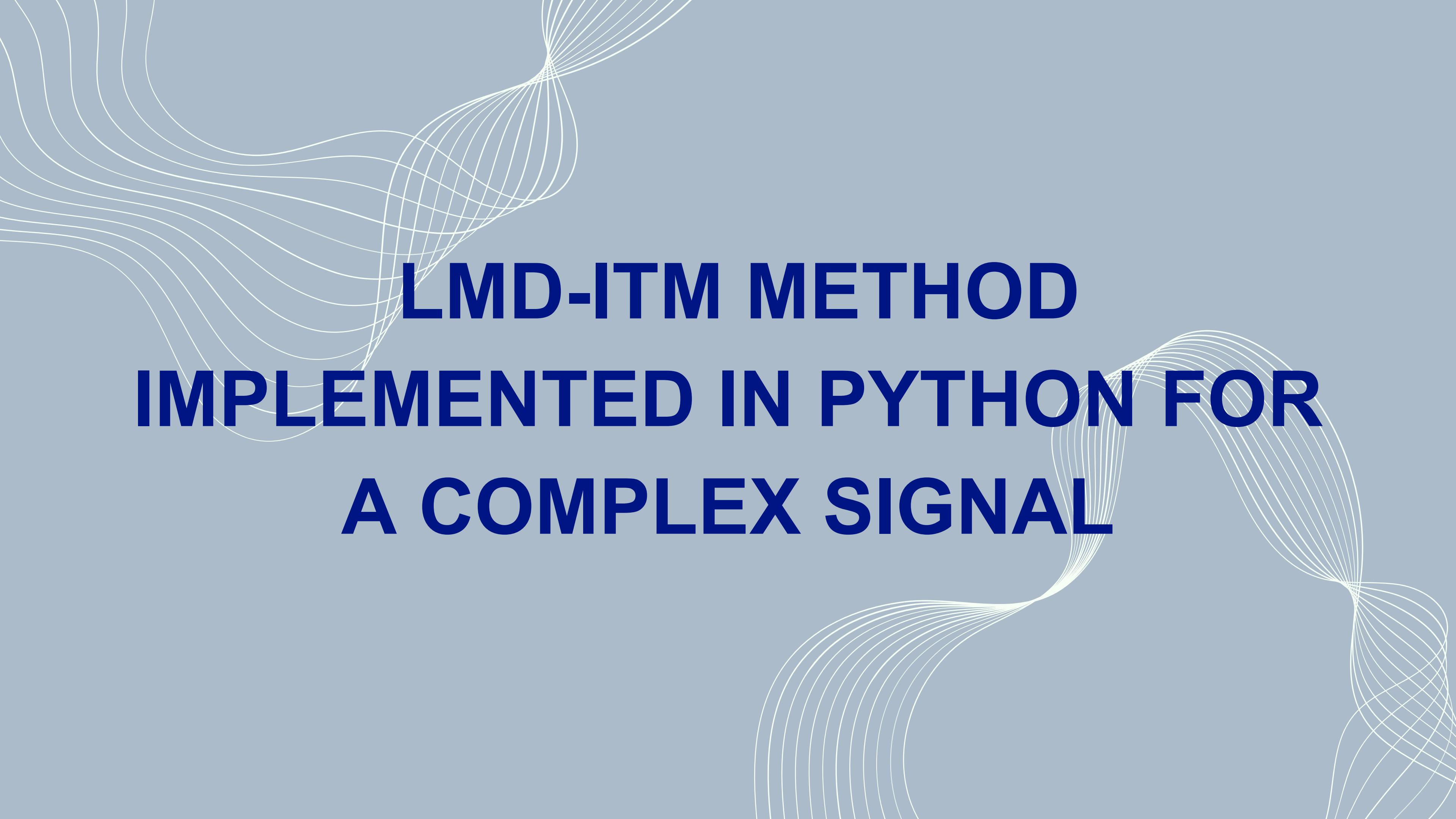
Iterative Thresholding Method (ITM):

- Initialization: The signal $x(t)$ and the threshold value λ are initialized.
- Thresholding: The thresholding operation is applied to the Product Function to obtain thresholded signal.
- Residue Calculation: The difference between the thresholded signal and the original signal is calculated to obtain the residue signal $r(t)$.

Setting of Thresholding value:

The parameters involved in setting the threshold value include:

- Peak Ratio (S)
- Adjustment Factor (β_p)
- Universal Threshold (λ_p)



LMD-ITM METHOD IMPLEMENTED IN PYTHON FOR A COMPLEX SIGNAL

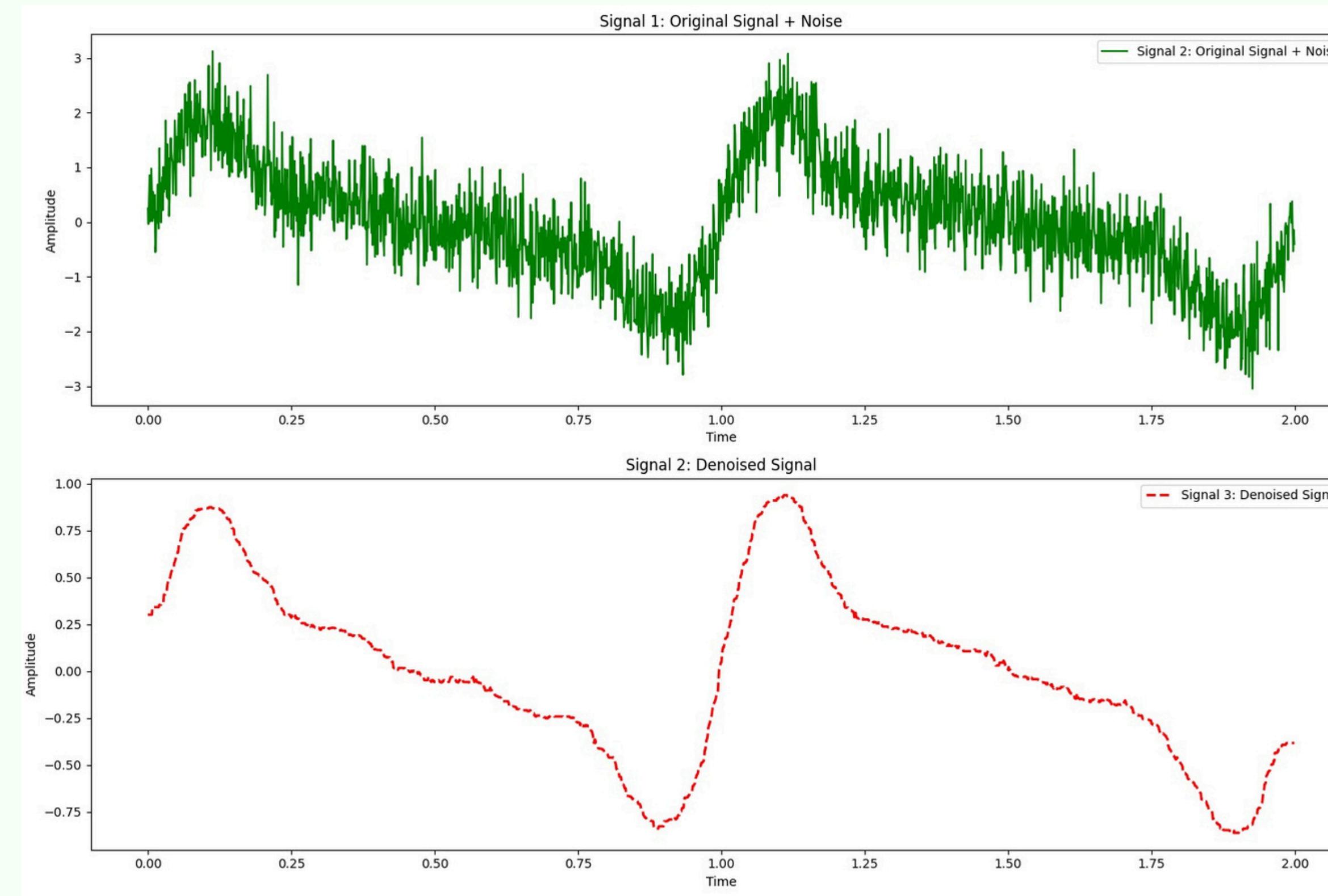


fig 4: Noise removal

RESULTS OBTAINED FOR DIFFERENT LIDAR DATASET

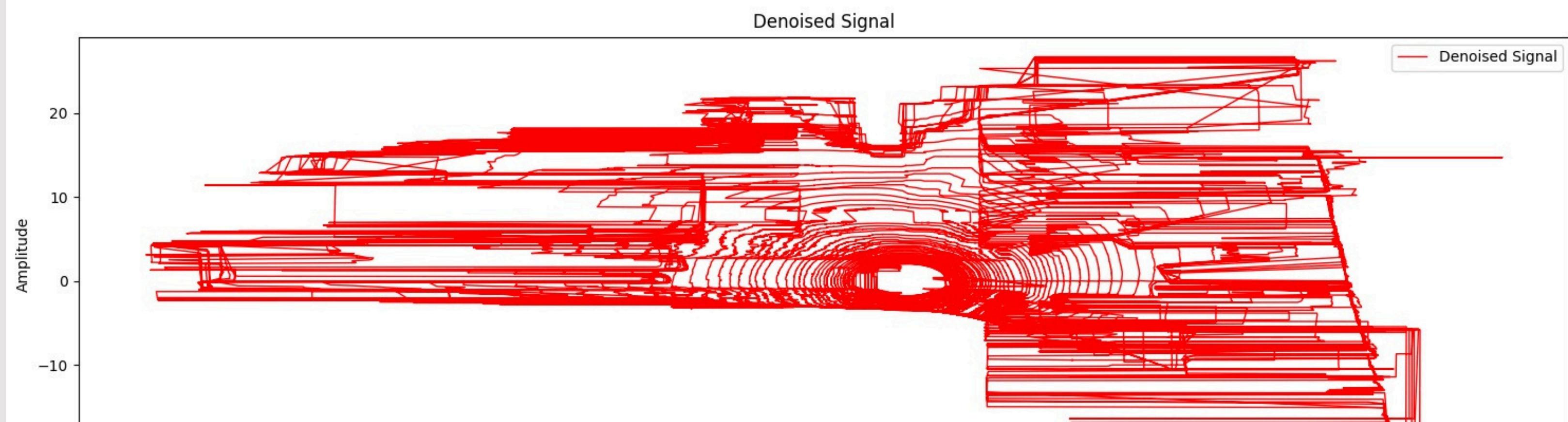
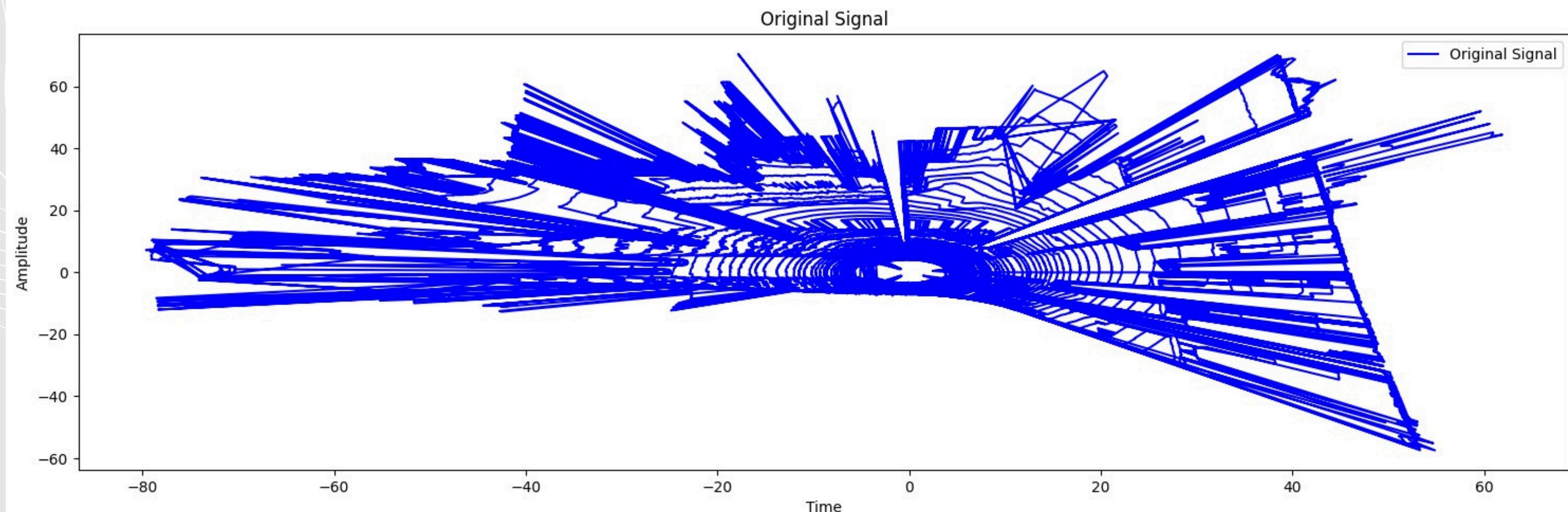


fig 6: Lidar dataset 1

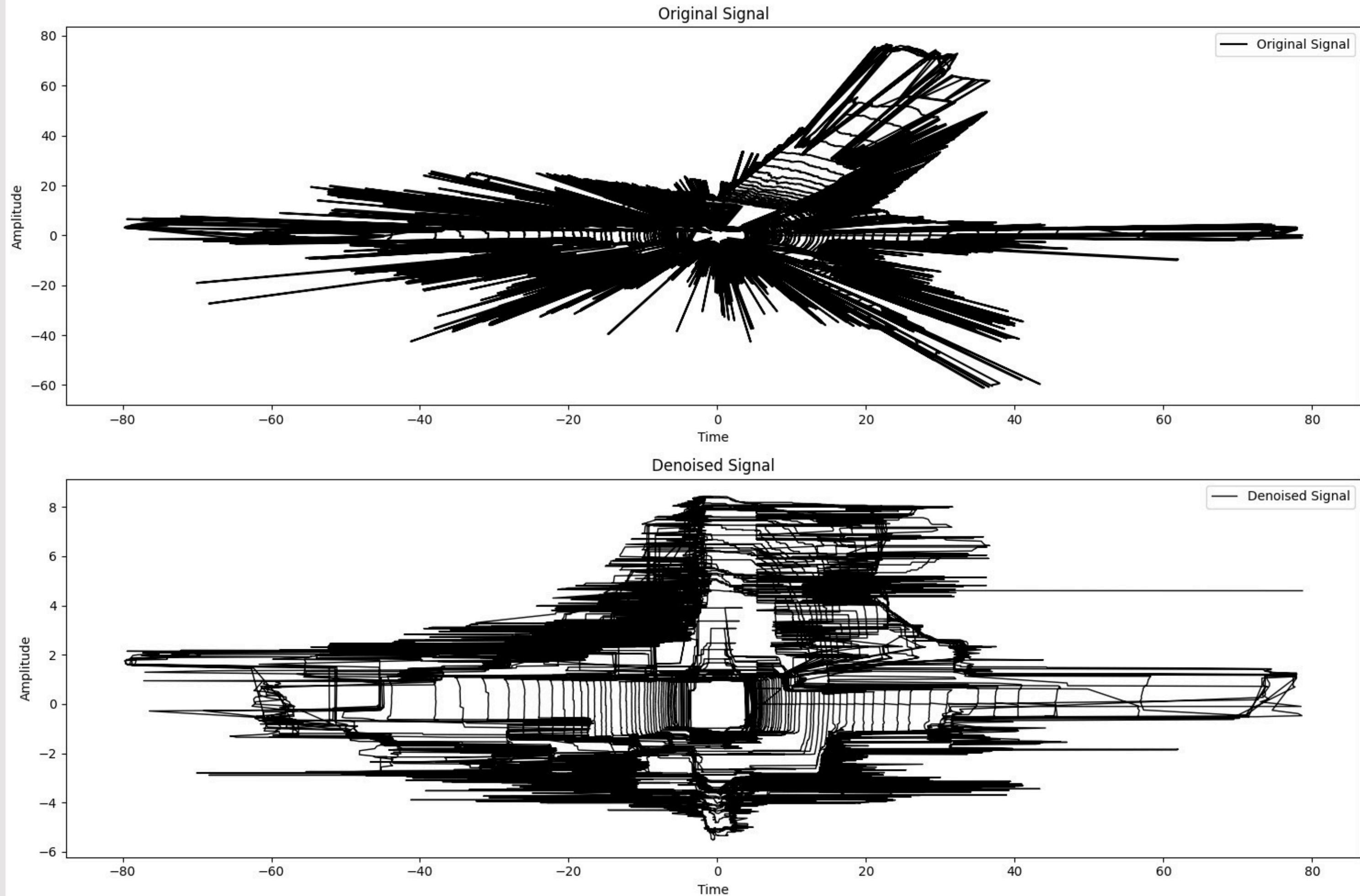


fig 7: lidar dataset 2

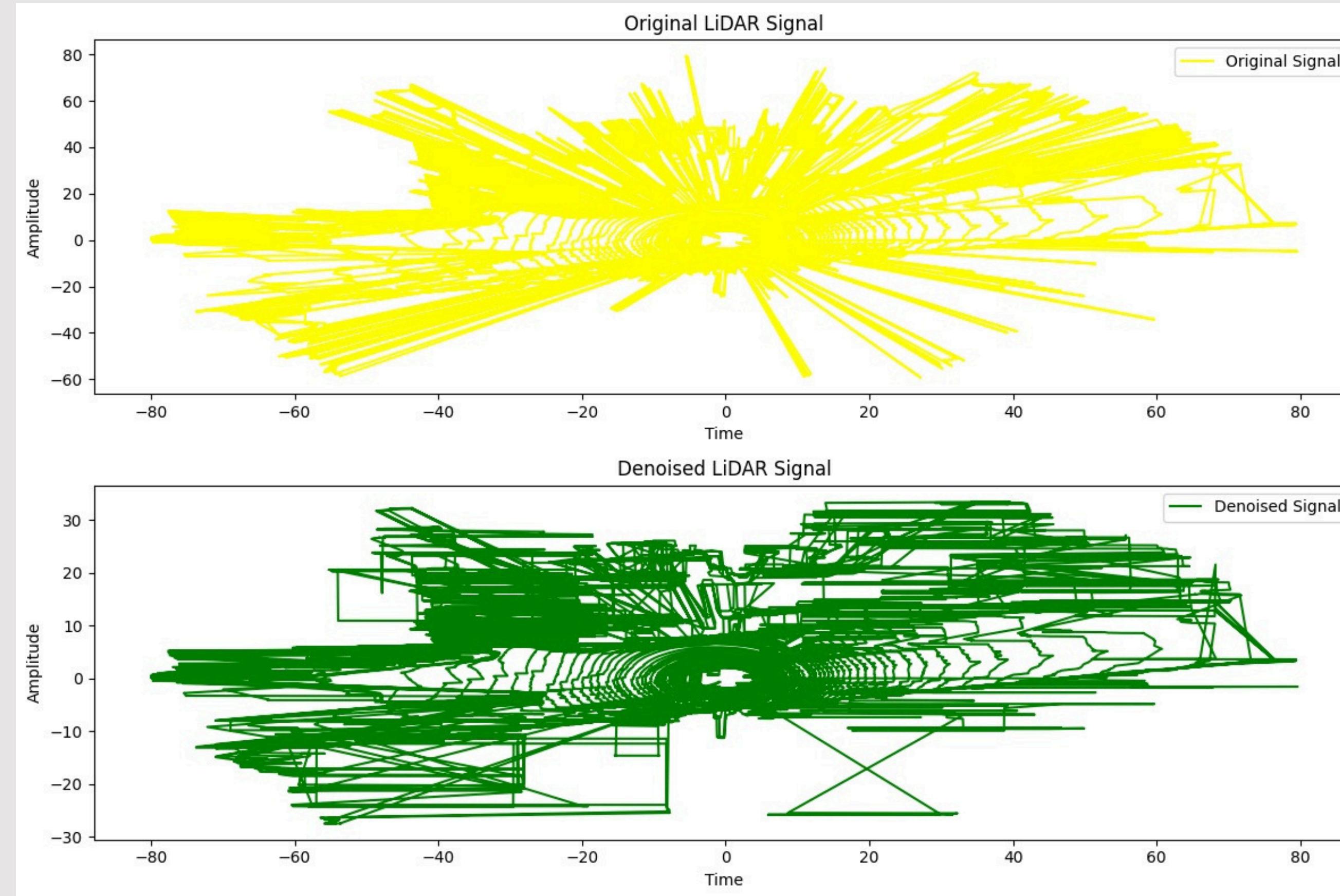


fig 7:Llidar dataset 3

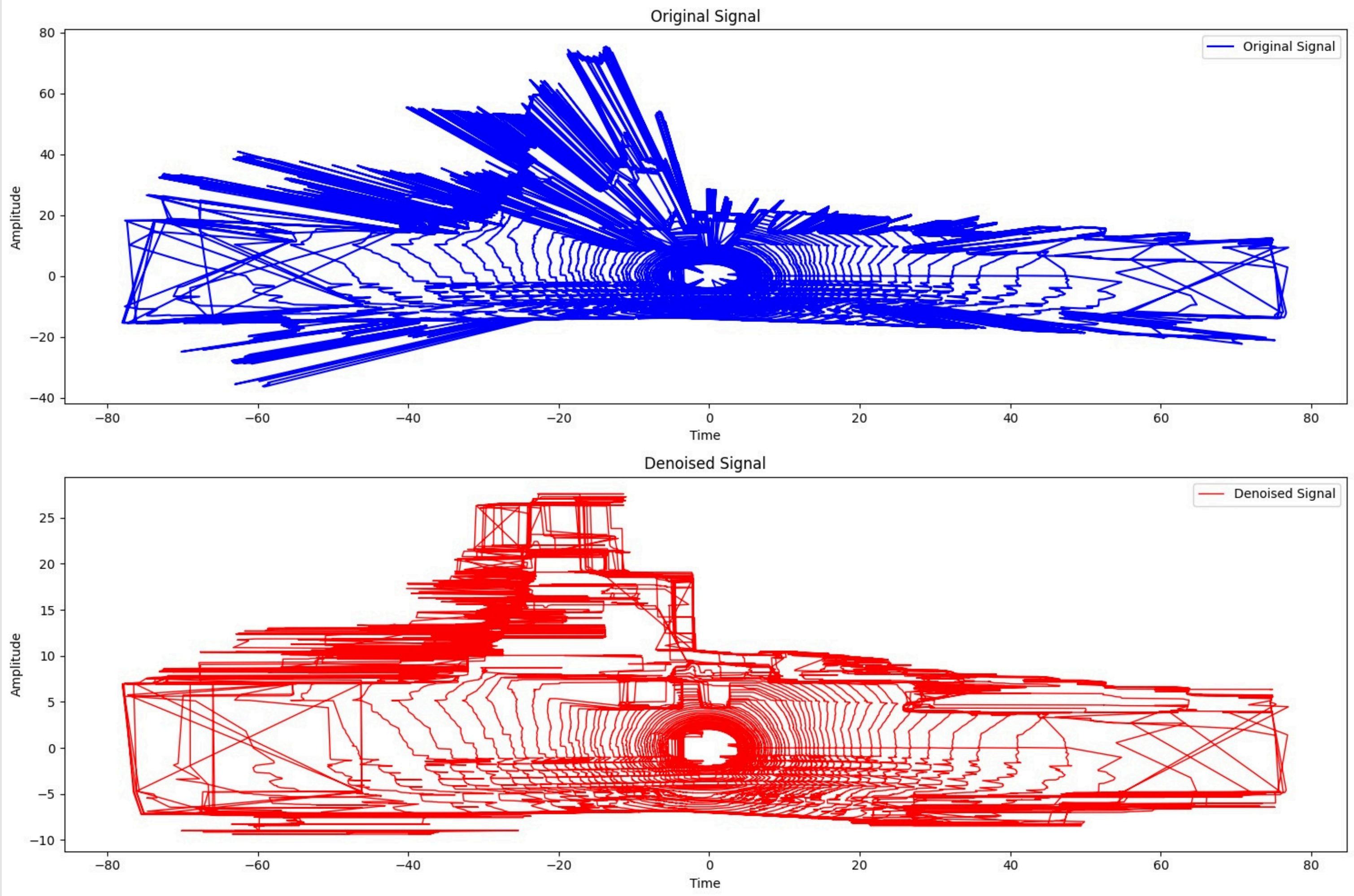


fig 7: lidar dataset 4

OUTPUT PLOT OBTAINED FOR IMPLEMENTATION IN PYNQ Z2

- Jupyter Notebook was used as interactive computational environment
- LMD-ITM algorithms were implemented, and their tracking results were visualized and compared
- ARM Cortex-A9 processors in PYNQ Z2 are utilized for executing this filter algorithms
- Execution times were compared with previous implementation



jupyter LMD_ITM Method Last Checkpoint: 3 hours ago (autosaved)



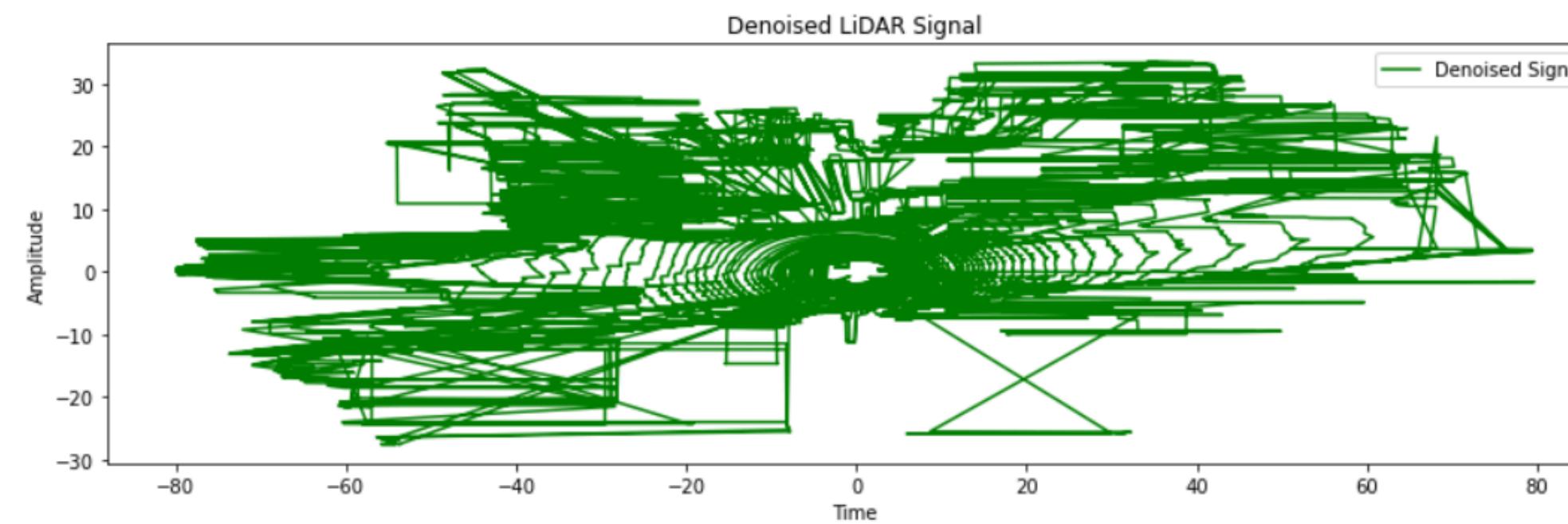
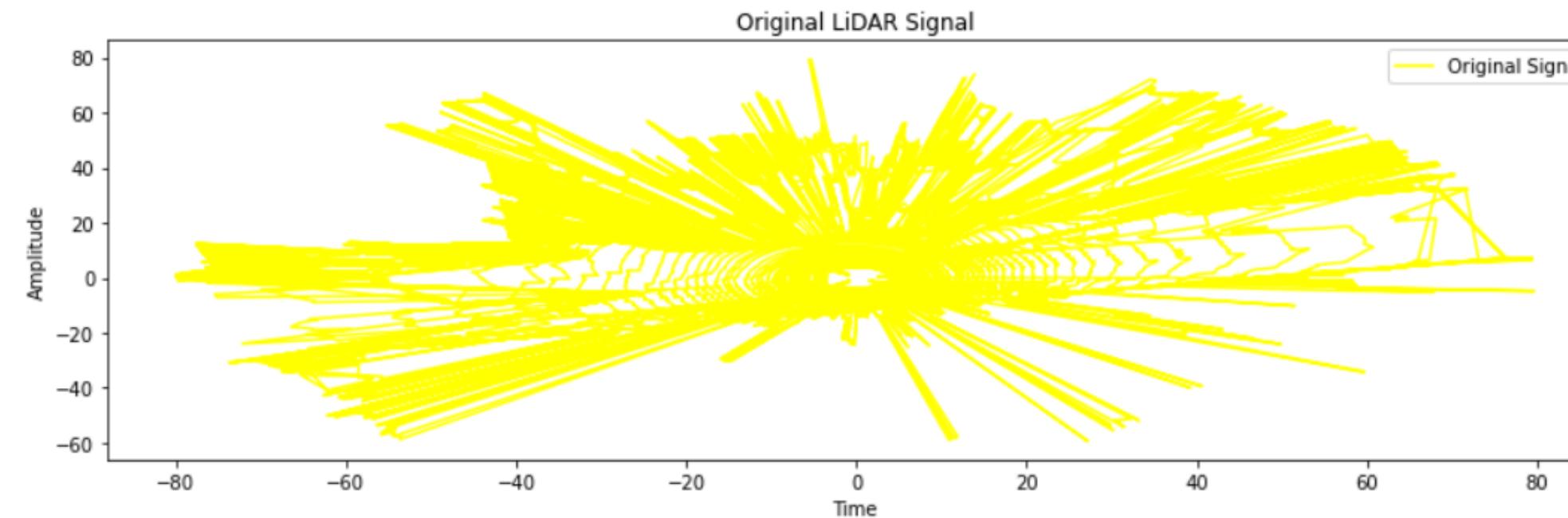
Logout

File Edit View Insert Cell Kernel Widgets Help

Not Connected Trusted | Python 3 (ipykernel)



Execution time for PYNQ-Z2 FPGA: 9.878823280334473 seconds



Activate Window
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fig 5: Output plot Obtained for implementation in PYNQ Z2

EXECUTION TIME COMPARISON :

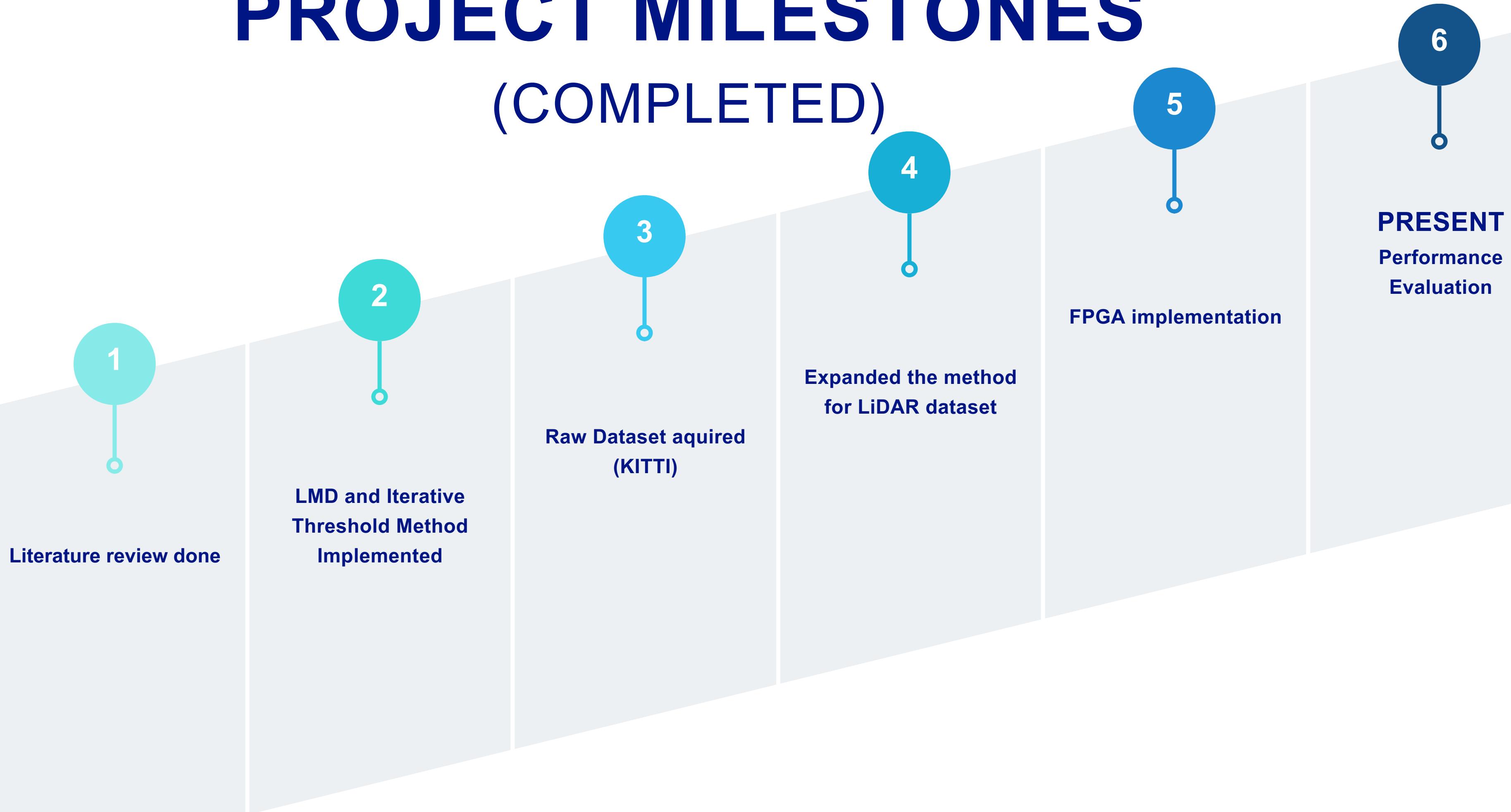
AMD Ryzen 7 vs PYNQ Z2

	AMD Ryzen 7	PYNQ Z2
LMD-ITM Filter	5 seconds	9.8788232 seconds

Table 1 : Comparison of Execution time of two processors

PROJECT MILESTONES

(COMPLETED)



FUTURE SCOPE

- Advanced FPGA Architectures
- Machine Learning on FPGA
- Real-time LiDAR Processing
- Integration with Other Sensors
- Scalable and Flexible FPGA Solutions
- Energy-efficient FPGA Designs
- Applications in Emerging Fields

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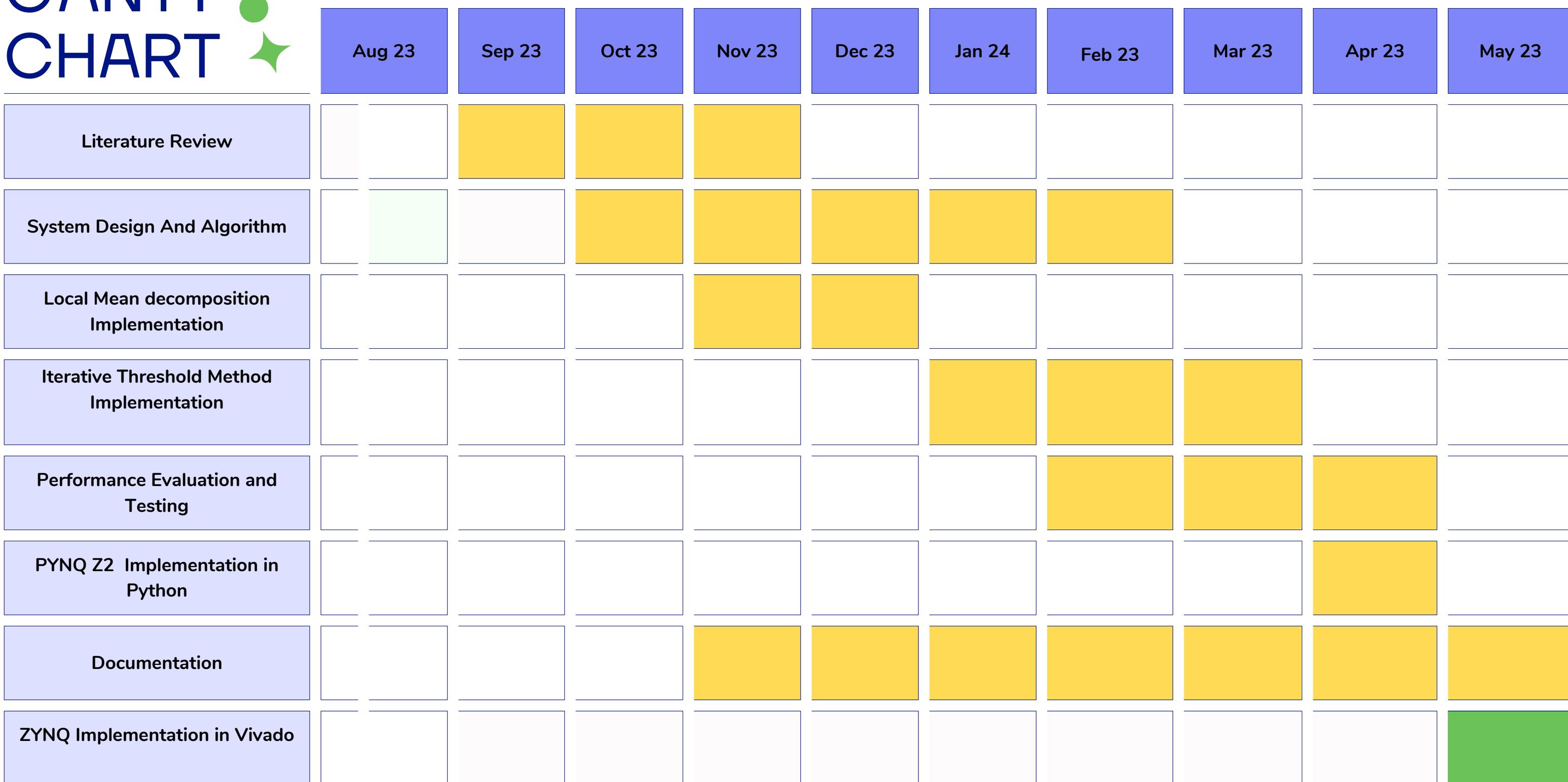
PROJECT GANTT CHART



WORKS COMPLETED



WORKS NOT COMPLETED



Work Division

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Dataset collection	Installation & Setup of python	Algorithm implementation and optimization of ITM	Architecture Design
Algorithm implementation in python	Algorithm Testing	PYNQ-Z2 implementation	Algorithm implementation of LMD-ITM Method
Performance Evaluation	Algorithm optimization of LDM method	Documentation	Performance Evaluation
PYNQ-Z2 implementation	Documentation	Performance Evaluation	Literature Review

**THANK'S
FOR
WATCHING**

