CSE1908 - Capstone Project
Final Review

SHRIMP FEEDING BEHAVIOUR ANALYSIS

IN COMPLEX AQUATIC AUDIO ENVIRONMENTS

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Guide: Dr. Suganya G

Contents

Introduction

This project focuses on analyzing audio signals to detect and differentiate between shrimp sounds (snapping and feeding) and insect noise. Using the Librosa library, we performed waveform analysis, spectrogram generation, MFCC extraction, and RMS energy analysis on three types of audio files:

1. NoNoise: Shrimp sounds only.
2. NoiseType1: Shrimp sounds with static noise.
3. NoiseType2: Shrimp sounds with insect noise.

We applied noise reduction techniques like spectral subtraction and wavelet denoising to enhance audio clarity. The spectrogram proved most effective for identifying insect noise at 7.5–8.5 kHz, while other tools helped analyze shrimp sounds. This project aims to improve noise reduction and sound detection for aquatic audio analysis.

LITERATURE REVIEW

No.	Title	Authors	Conference	Year	Key Contributions
1	Sound Emission of Macrobrachium rosenbergii During Feeding Activity	Hamilton, M., et al.	Aquaculture Research	2021	Examined sound patterns during feeding of giant freshwater prawns, providing foundational data for acoustic-based feeding systems.
2	Recognition of Feeding Sounds of Large-Mouth Black Bass	Cao, Y., et al.	Frontiers in Marine Science	2024	Identified feeding sounds in fish using low-dimensional acoustic features, methods applicable to shrimp sound detection.
3	A Multi-View CNN-Based Acoustic Classification System	Xu, W., et al.	arXiv preprint	2020	Proposed a CNN-based system for classifying animal sounds, highlighting potential for shrimp feeding noise differentiation.
4	Advanced Framework for Animal Sound Classification with Features	Yang, Q., et al.	arXiv preprint	2024	Developed a feature optimization framework for classifying animal sounds, improving recognition in noisy environments.
5	Identification of soft shell shrimp based on deep learning	Z Lieu.,et al.	American Society of Agricultural and Biological Engineers	2016	Deep learning architectures like Deep Belief Networks and Sparse Autoencoders have demonstrated success in vision and language tasks by learning hierarchical data representations, reducing the need for manual feature engineering.

No.	Title	Authors	Conference/Journal	Year	Key Contributions
6	Use of passive acoustic monitoring to evaluate the effects of a feed effector on feeding behavior, growth performance, and salinity stress tolerance of *Litopenaeus vannamei*	Smith, M., & Tabrett, S.	Aquaculture	2019	Explored the potential of passive acoustic monitoring (PAM) to track feeding activity in shrimp aquaculture.
7	Application of Machine Learning in Aquaculture	Li, X., et al.	Aquaculture International	2022	Reviewed ML applications in aquaculture, including feeding systems, with a focus on automation and efficiency.
8	Recent Advances and Applications of Passive Acoustic Monitoring in Assessing Shrimp Feeding Behaviour Under Laboratory and Farm Conditions	Peixoto, S., et al	Reviews in Aquaculture	2020	Investigated combining acoustic monitoring and ML for automated fish feeding, applicable for shrimp aquaculture.
9	An intelligent management system for shrimp aquaculture using the IoT technology	NH Thong	Aquacultural Engineering	2023	Designed an intelligent feeding system leveraging environmental and behavioral cues, including sound.
10	Open-Source Pipeline for Noise-Resilient Voice Data Preparation	Patel, S., & Kumar, R.	Ecological Informatics	2021	Evaluated ML techniques for animal sound classification in noisy settings, relevant to shrimp feeding scenarios.

No.	Title	Authors	Conference	Year	Key Contributions
11	Cross-correlation based Acoustic Signal Processing Technique and its Implementation on Marine Ecology	SM Hossain	IEEE Access	2019	Reviewed challenges and techniques for underwater acoustic signal processing, offering guidance for robust shrimp feeding systems.
12	Improving deep learning acoustic classifiers with contextual information for wildlife monitoring	Jeantet, L.,Et al	Elviser	2023	Explored deep learning applications for bioacoustic monitoring, useful for shrimp feeding sound identification.
13	Monitoring methods of feeding behaviour to answer key questions in penaeid shrimp feeding	JB Darodes de Tailly., Et al	Aquaculture Engineering	2022	Applied ML algorithms to monitor shrimp feeding sounds, demonstrating effectiveness in noisy environments.
14	Enhancing automated analysis of marine soundscapes using ecoacoustic indices and machine learning	Nguyen, T., et al.	Computers and Electronics in Agri.	2023	Integrated PAM and ML to optimize feed management, showcasing a framework applicable for shrimp aquaculture.
15	Acoustic characterization of feeding activity of Litopenaeus vannamei in captivity	S Hamilton.,Et al	Aquaculture Research	2021	Characterized shrimp feeding sounds, providing critical data for automated acoustic feeding systems.

Scope and Problem Statement

SCOPE

- Shrimp Feeding Behavior Analysis via Audio
- Noise Reduction and Feature Extraction: Test noise reduction on three audio files (NoNoise, NoiseType2, NoiseType1)

PROBLEM STATEMENT

- How can we detect shrimp feeding behavior when static noise obscures subtle aquatic sounds?
- Over-filtering distorts key signals, and frequencies remain unclear.

Research Challenges

01

Isolating Shrimp Feeding Sounds: Focus on extracting shrimp feeding sounds from static noise, such as the "middle bar" in NoiseType1.

02

Detecting Subtle Signals: Identify potential insect noise without excessive filtering that could remove important shrimp feeding sounds.

03

Defining Frequency Ranges: Establish consistent frequency ranges for shrimp snapping and feeding to improve detection accuracy.

04

Balancing Noise Reduction: Optimize noise reduction to retain essential aquatic features while minimizing interference, despite limited audio samples for confirming insect presence.

Research Objectives

Shrimp Detection

Develop a method to detect shrimp feeding behavior in noisy aquatic audio.

Noise Isolation

Isolate shrimp snapping and feeding sounds from static interference.

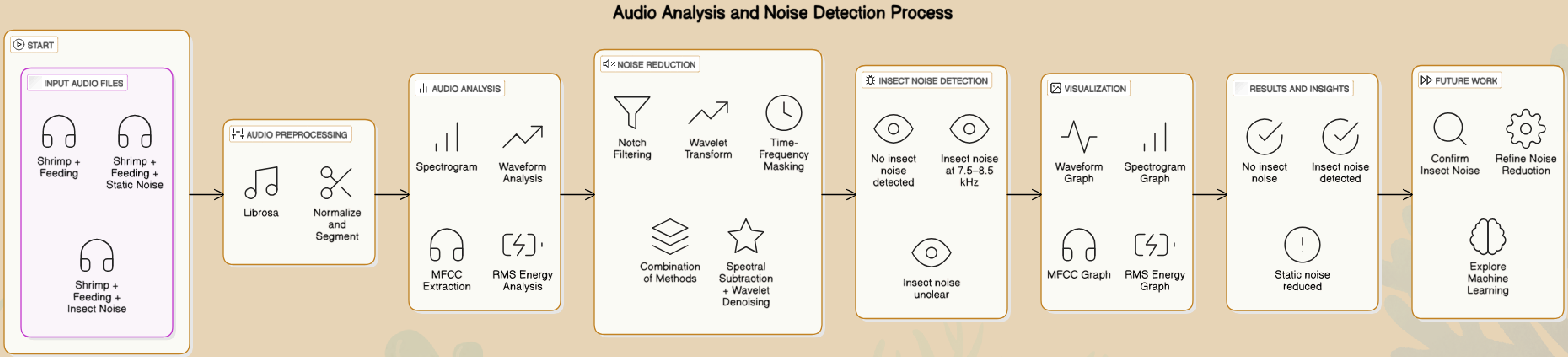
Subtle Noise Analysis

Identify the presence of subtle noises (e.g., insects) using spectrogram analysis.

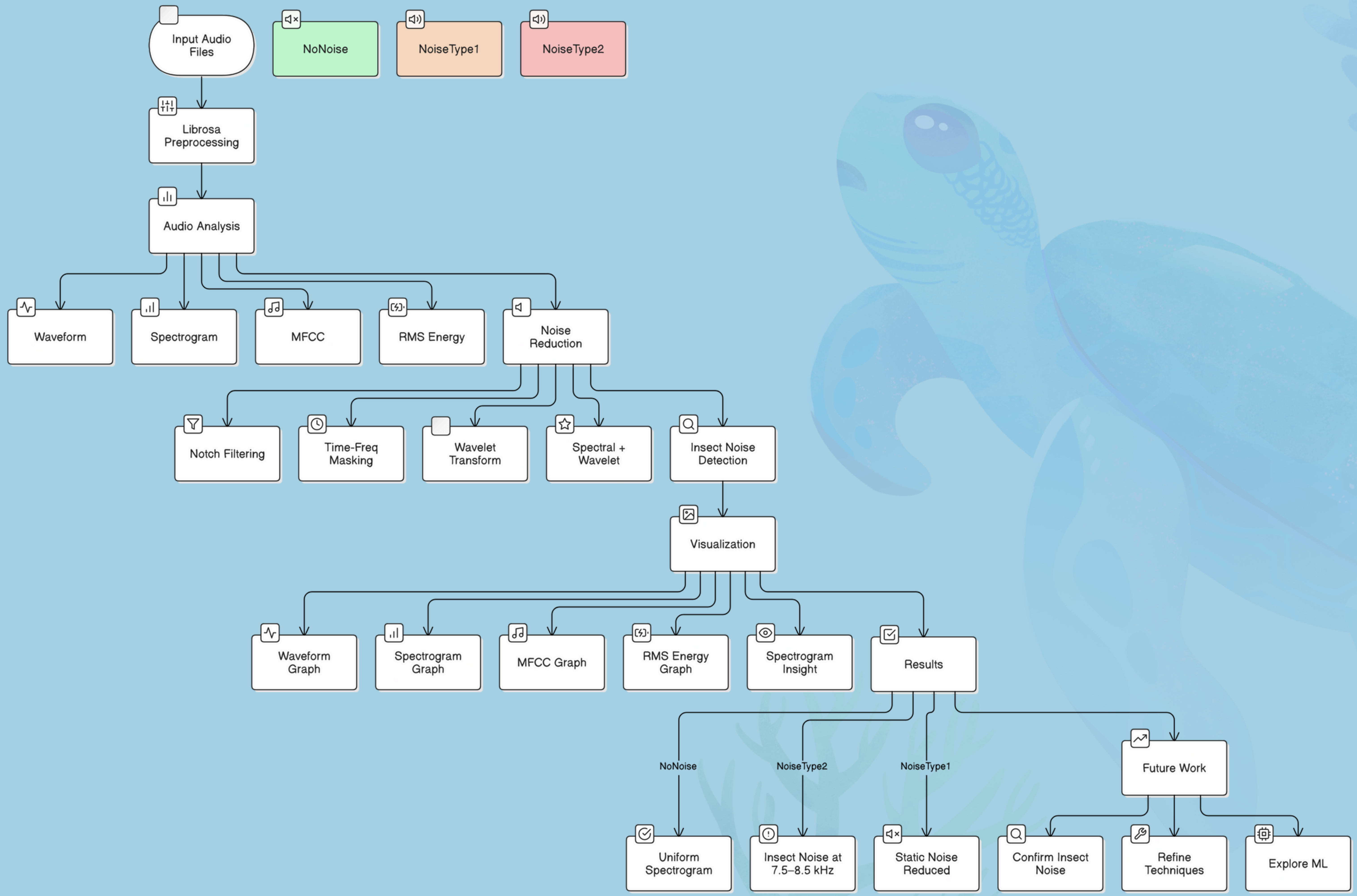
Frequency Characterization

Achieve noise-robust frequency characterization for shrimp sounds.

Methodology



Audio Processing Flowchart



CPS (Clicks Per Second)

CPS represents how frequently shrimp clicks occur per second in the underwater recording.
For a 1-second frame, this is simply the number of detected peaks.
Audio Input:

- The system loads an underwater audio file sampled at 44.1 kHz.

Preprocessing:

- A bandpass filter (2000–6000 Hz) is applied to isolate relevant frequency components (likely shrimp clicks).

Click Detection:

- Uses scipy.signal.find_peaks to detect acoustic peaks that surpass a given amplitude threshold and occur with sufficient temporal spacing (10 ms apart).

CPS Calculation:

- CPS (Clicks Per Second) is calculated by counting peaks in 1-second frames.
- Smoothing is applied using a moving average window (size 5).

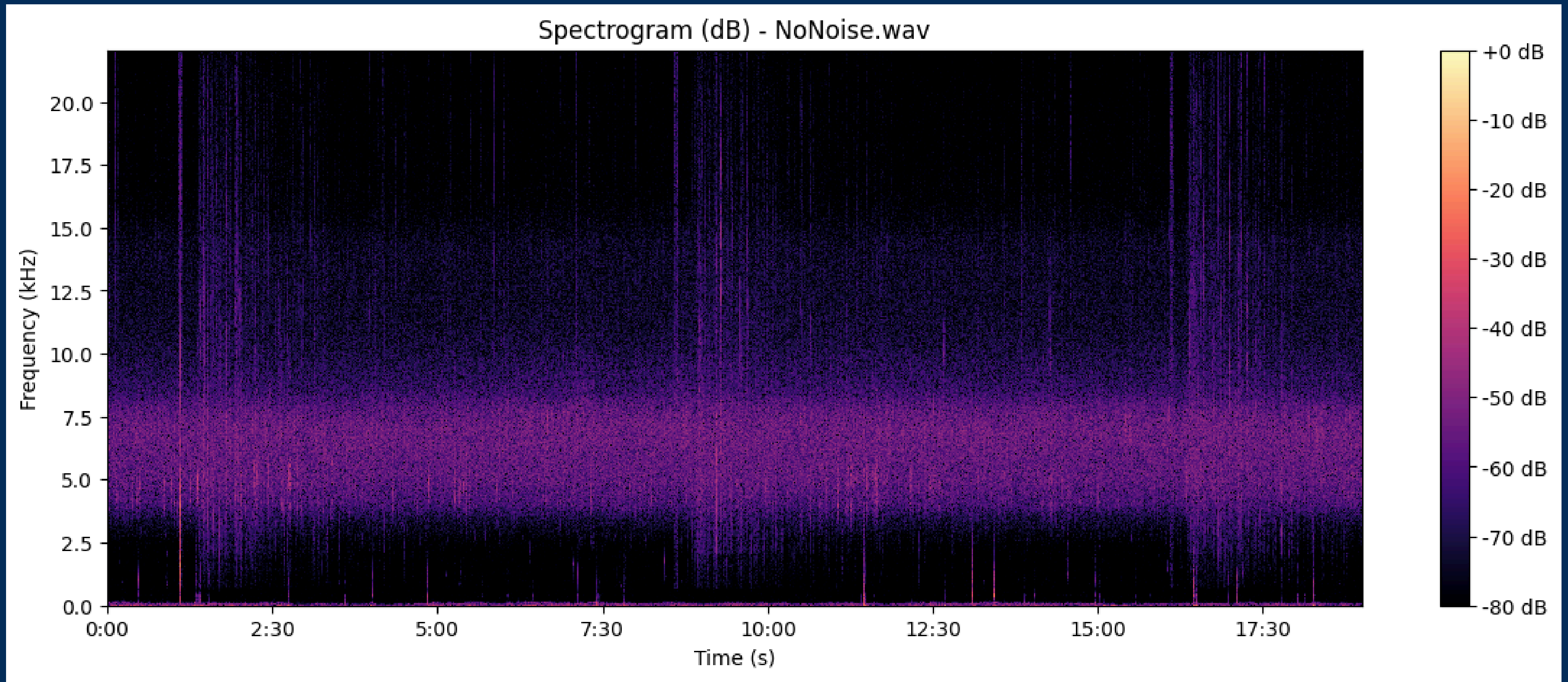
Visualization and Stats:

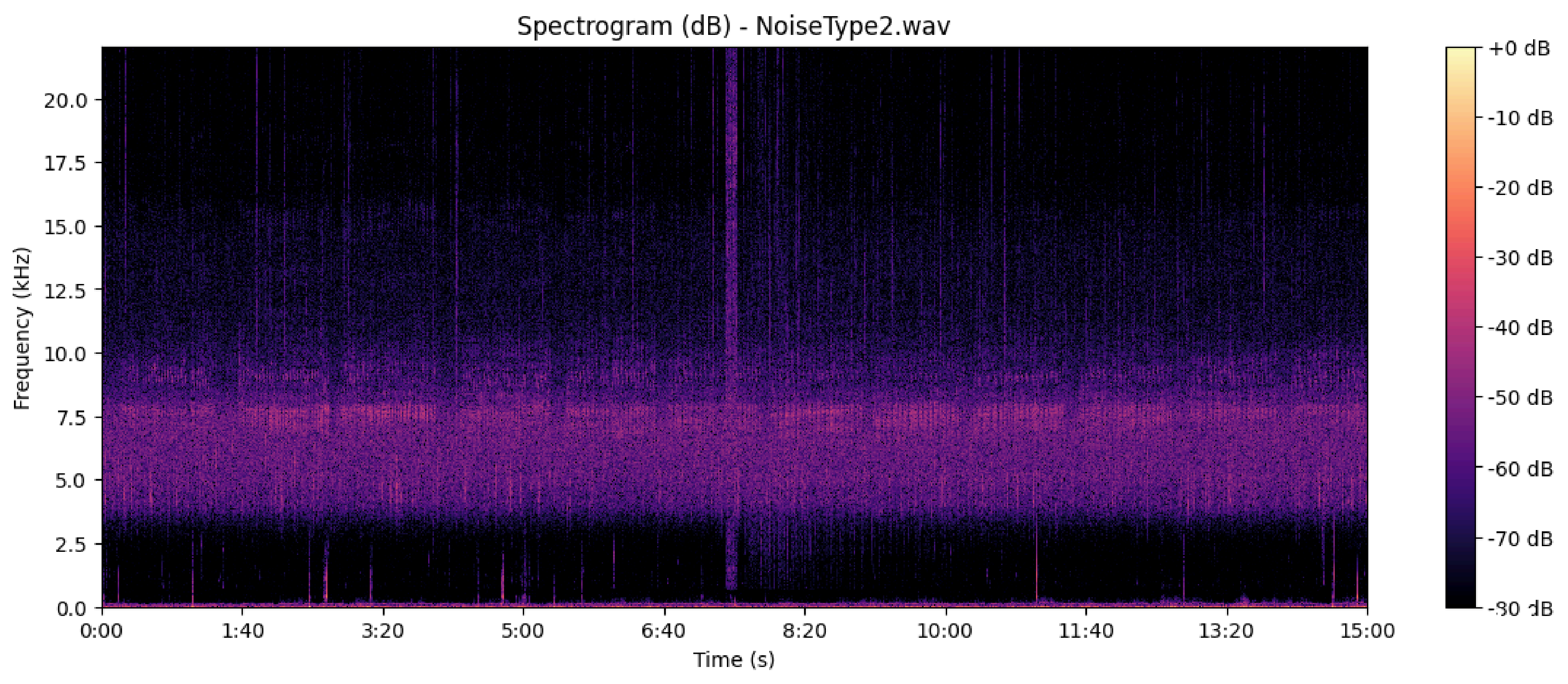
- CPS is plotted over time.
- Key statistics such as average, max, min CPS, and frame counts above thresholds (≥5, ≥10) are printed.

Results and Discussion

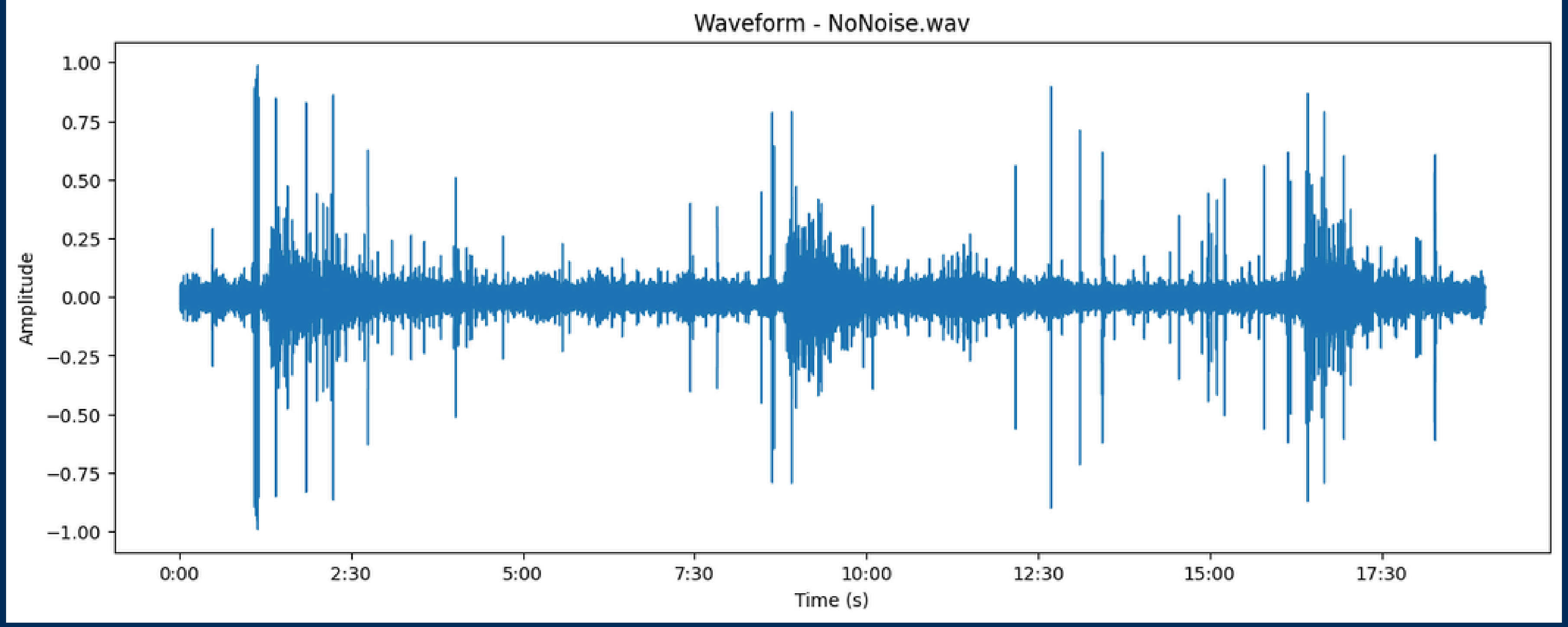
Spectrogram Analysis

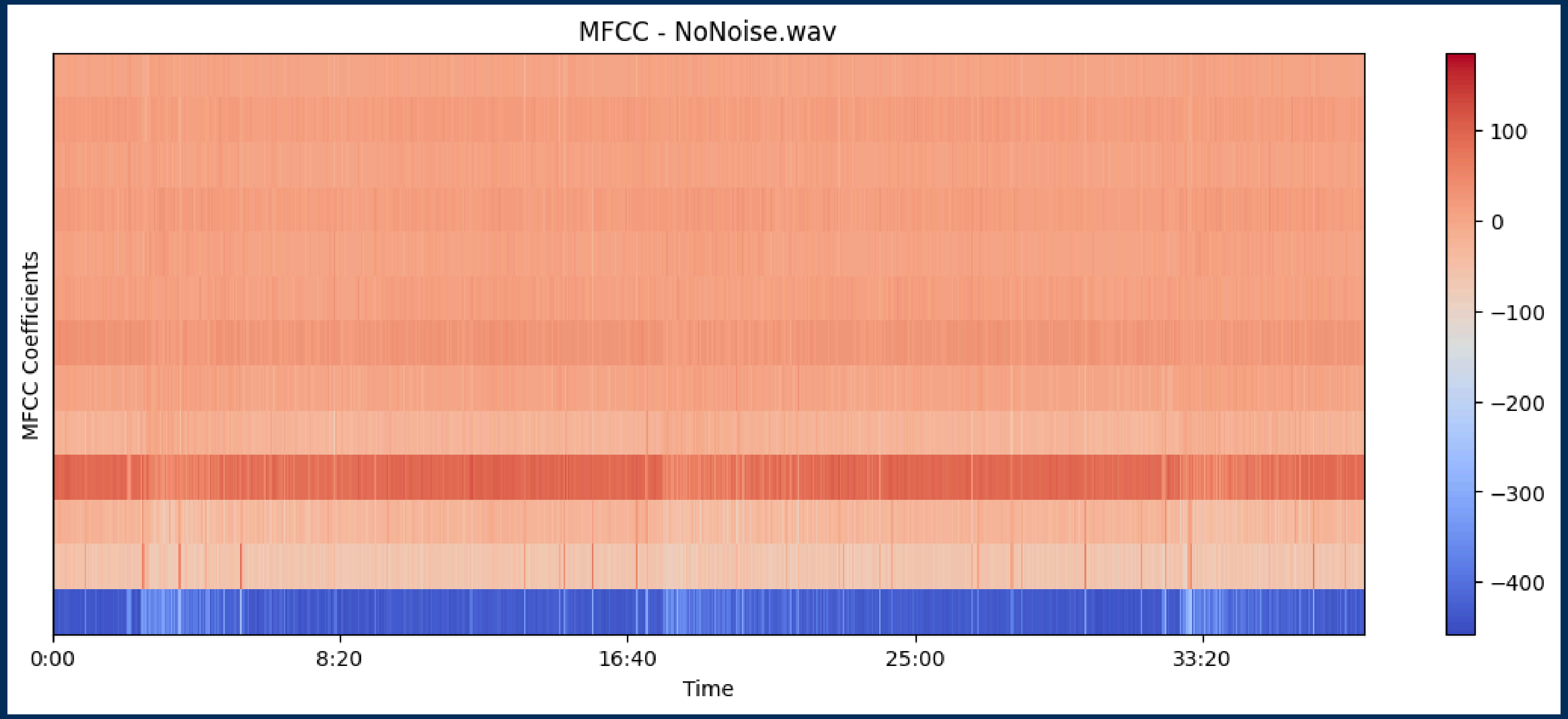
- NoNoise:
  - The spectrogram is uniform.
  - No pattern at 7.5 kHz because there is no insect noise in this audio.
- NoiseType2:
  - The highlighted intensity in the spectrogram is insect noise.
  - Insect noise is consistently in the range of 7.5–8.5 kHz throughout the audio.
- Inference:
  - Only the spectrogram shows a clear pattern for insect noise, visualized as high-intensity values at 7.5–8.5 kHz.

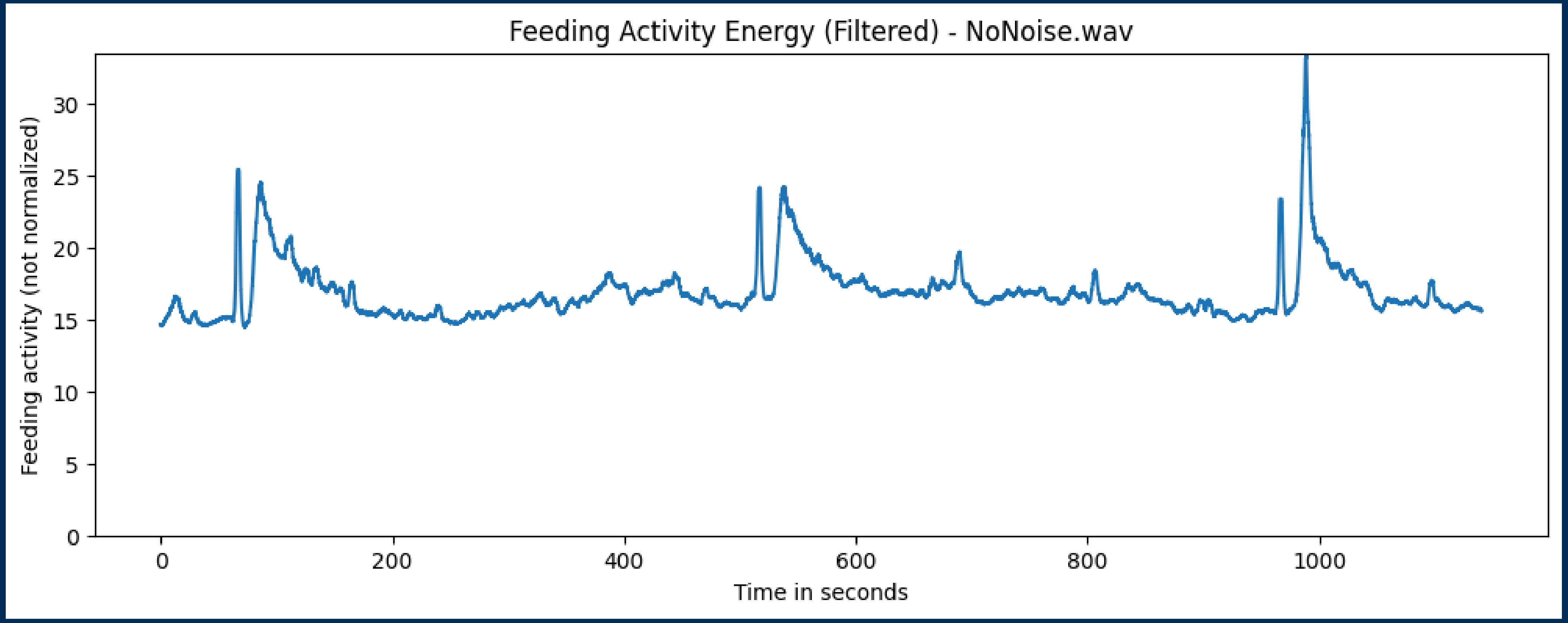




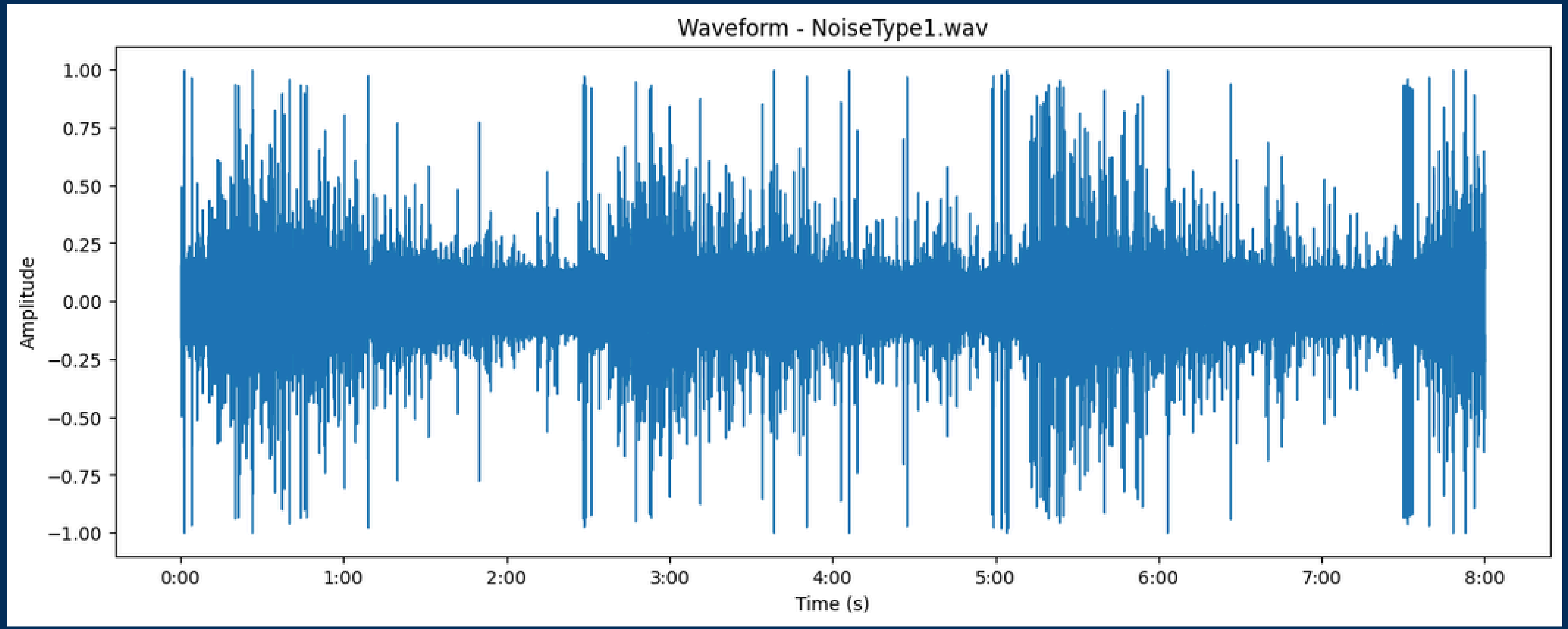
Results and Discussion

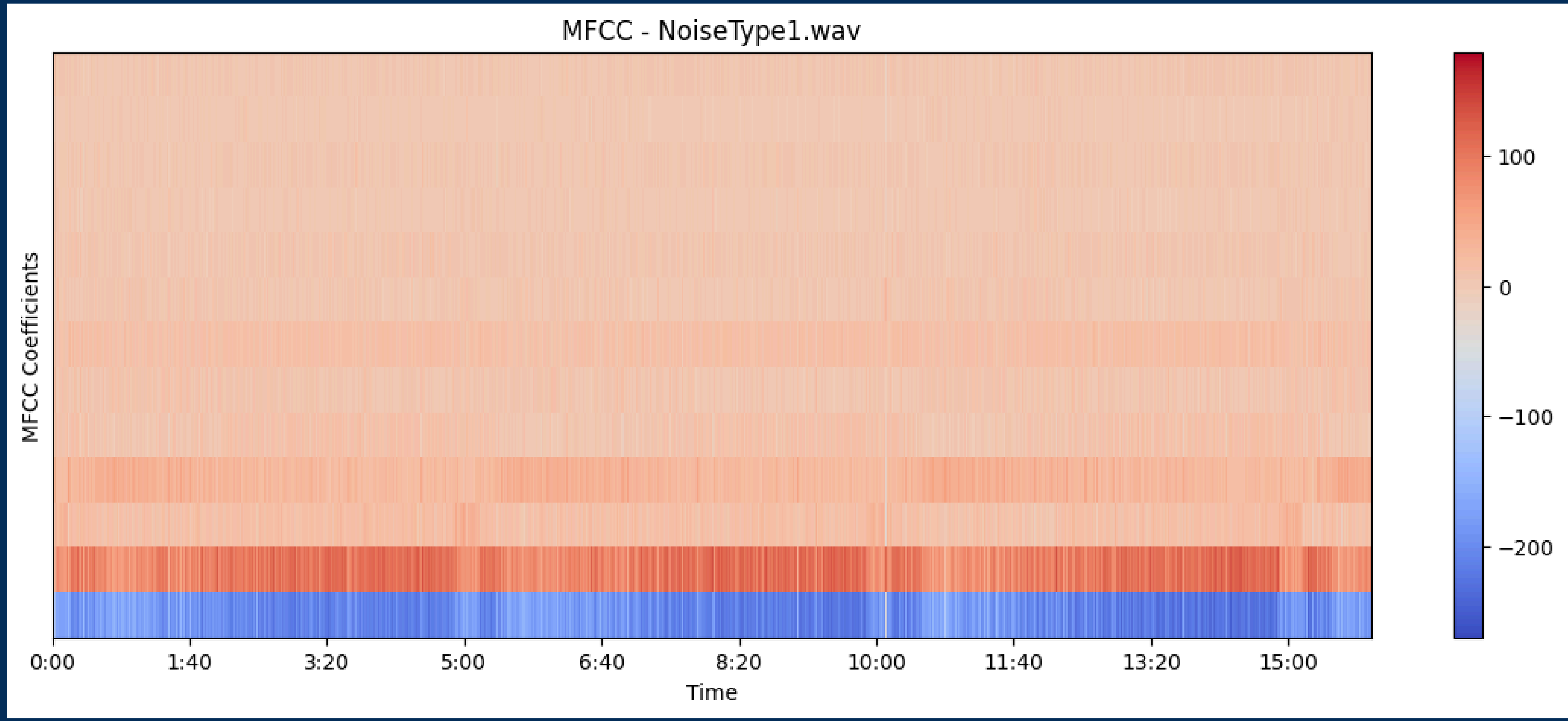


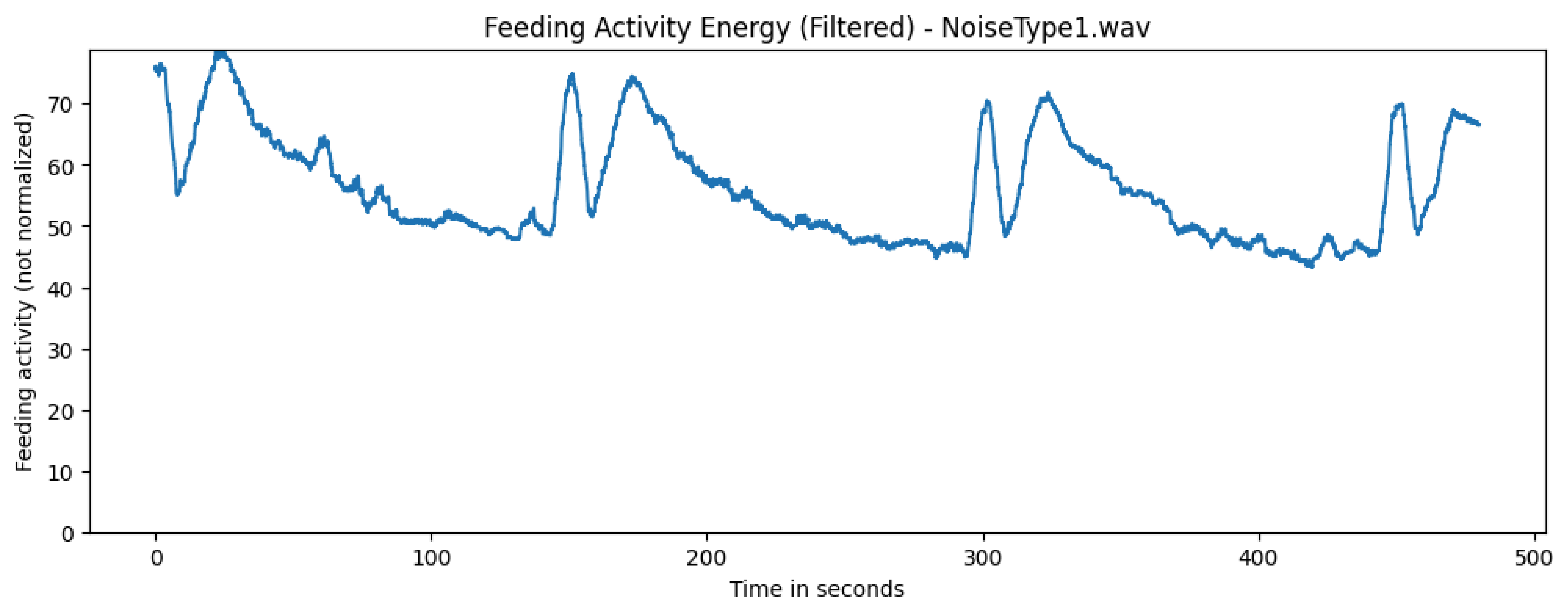




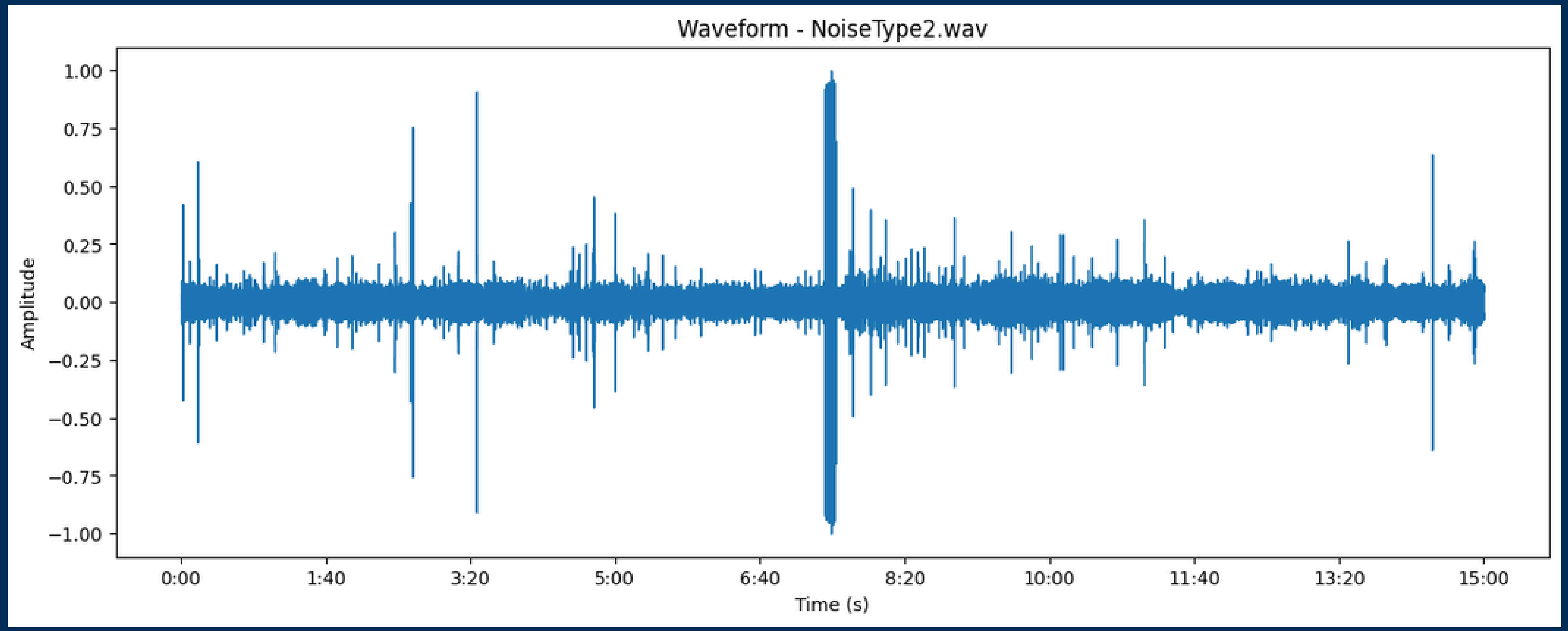
Results and Discussion

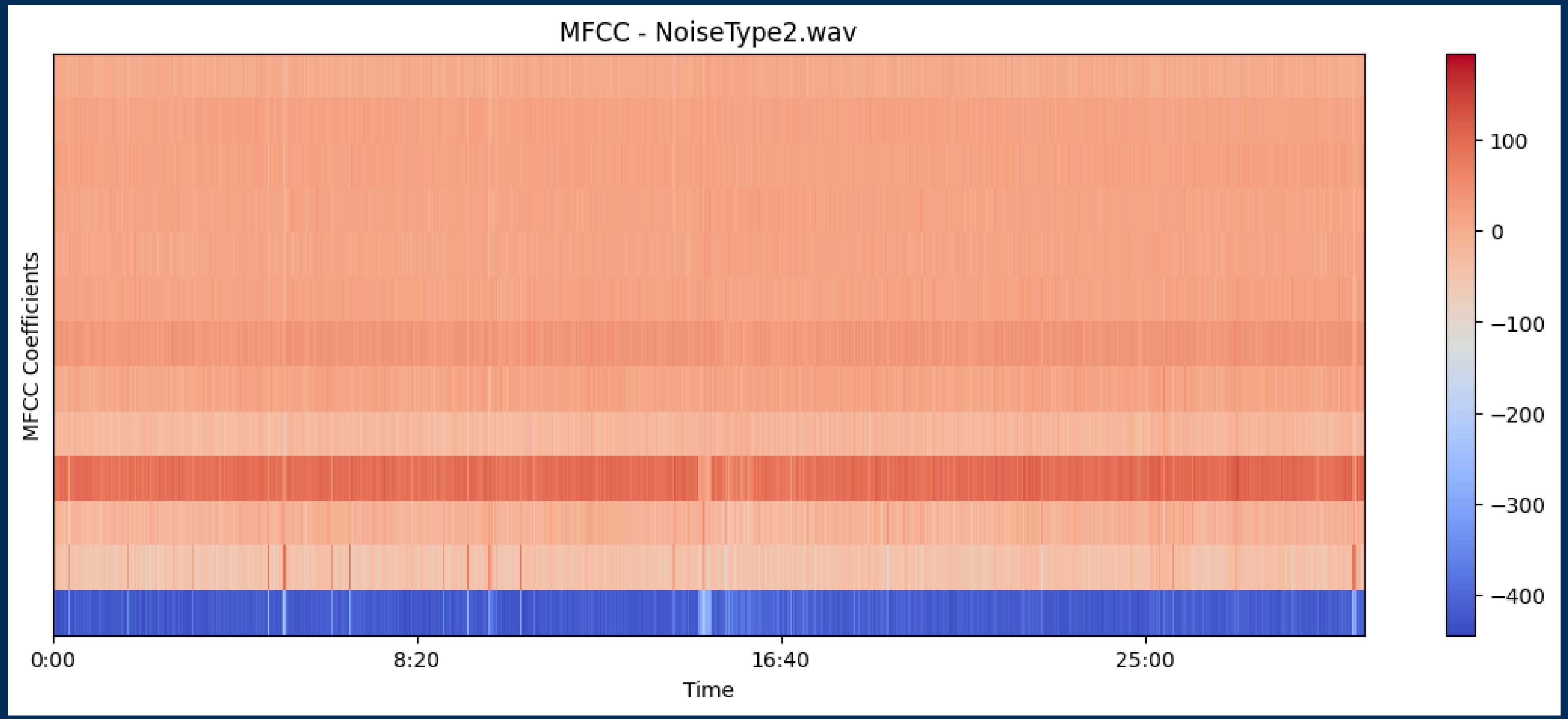


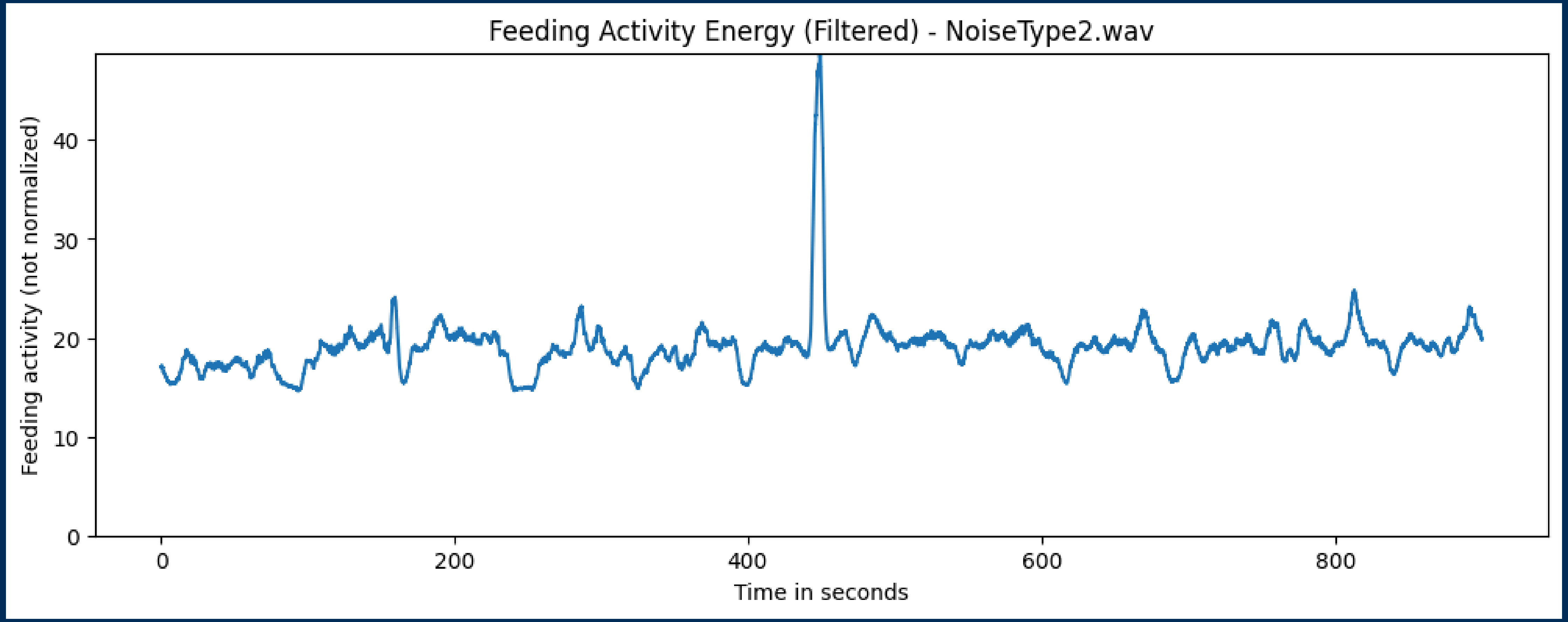




Results and Discussion



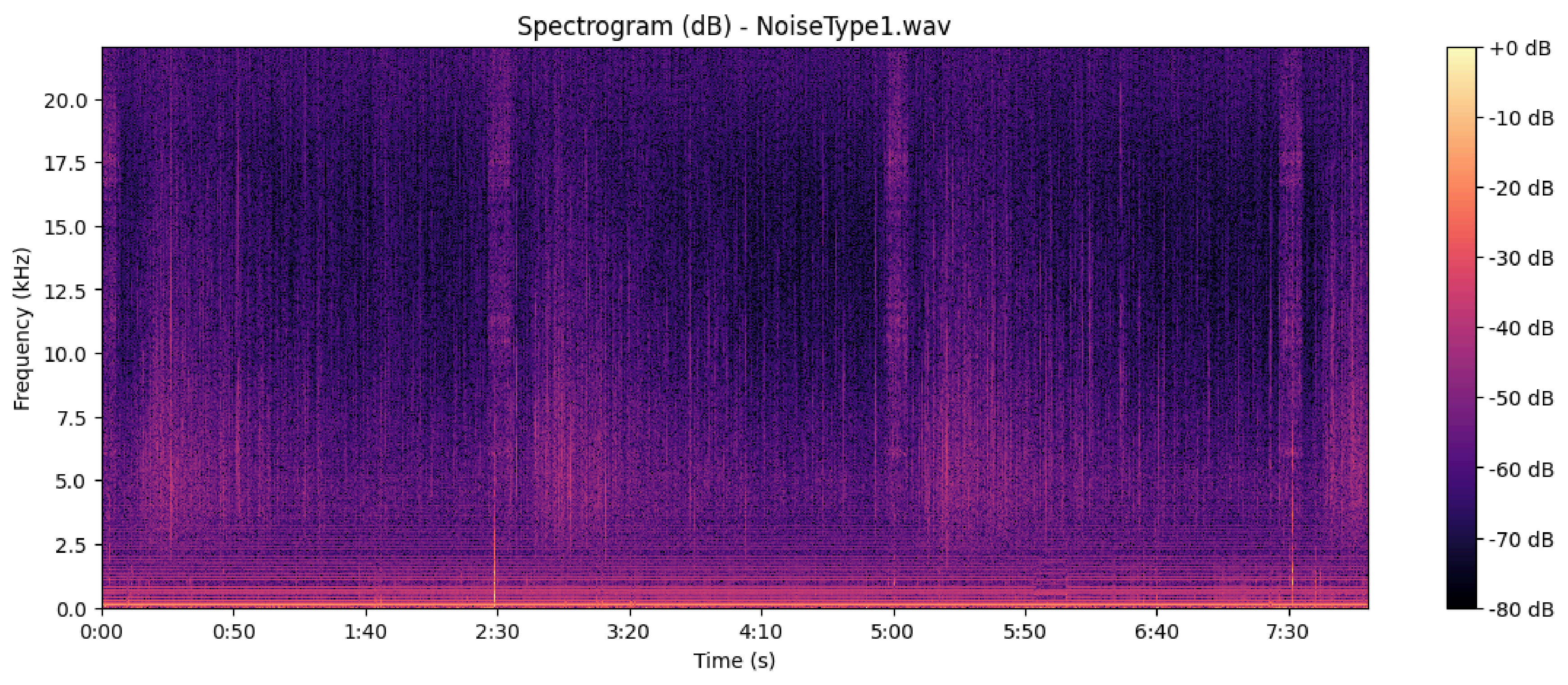


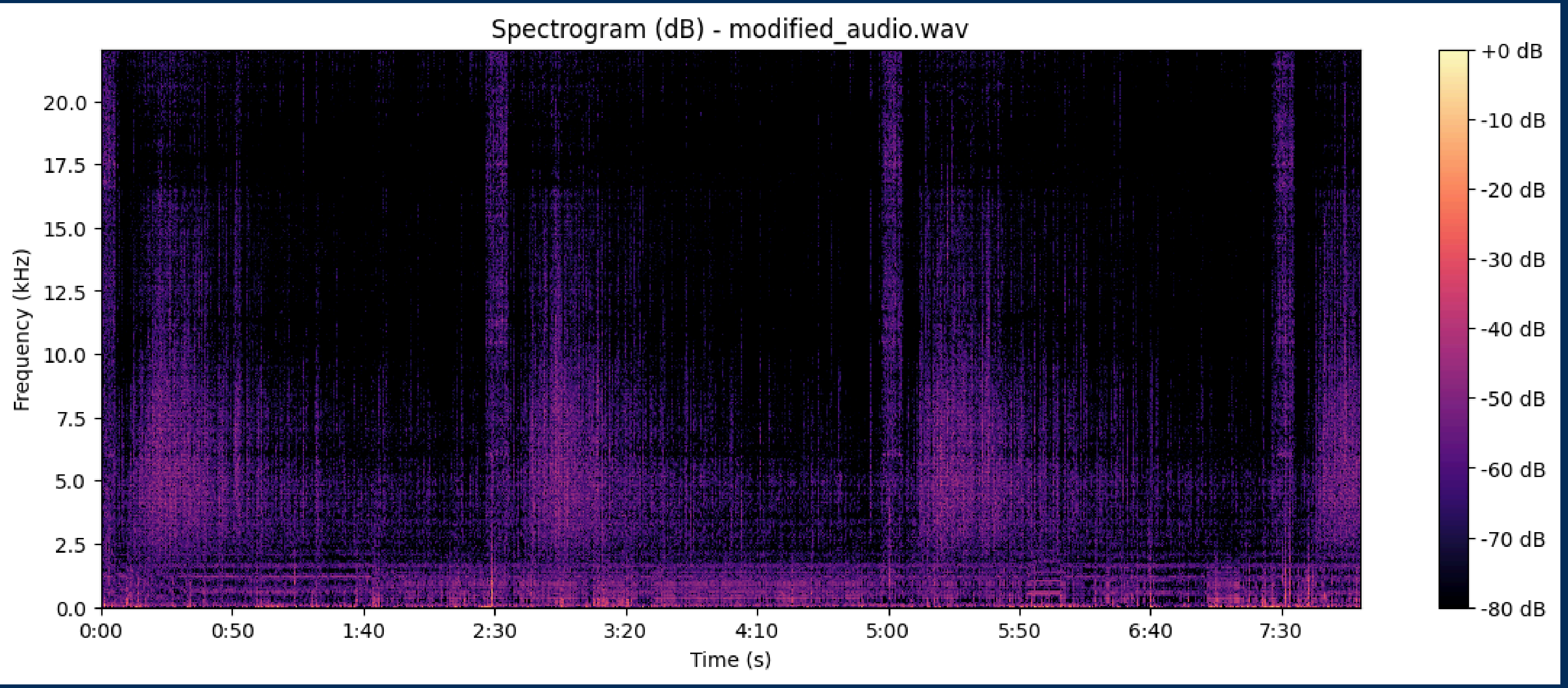


Results and Discussion

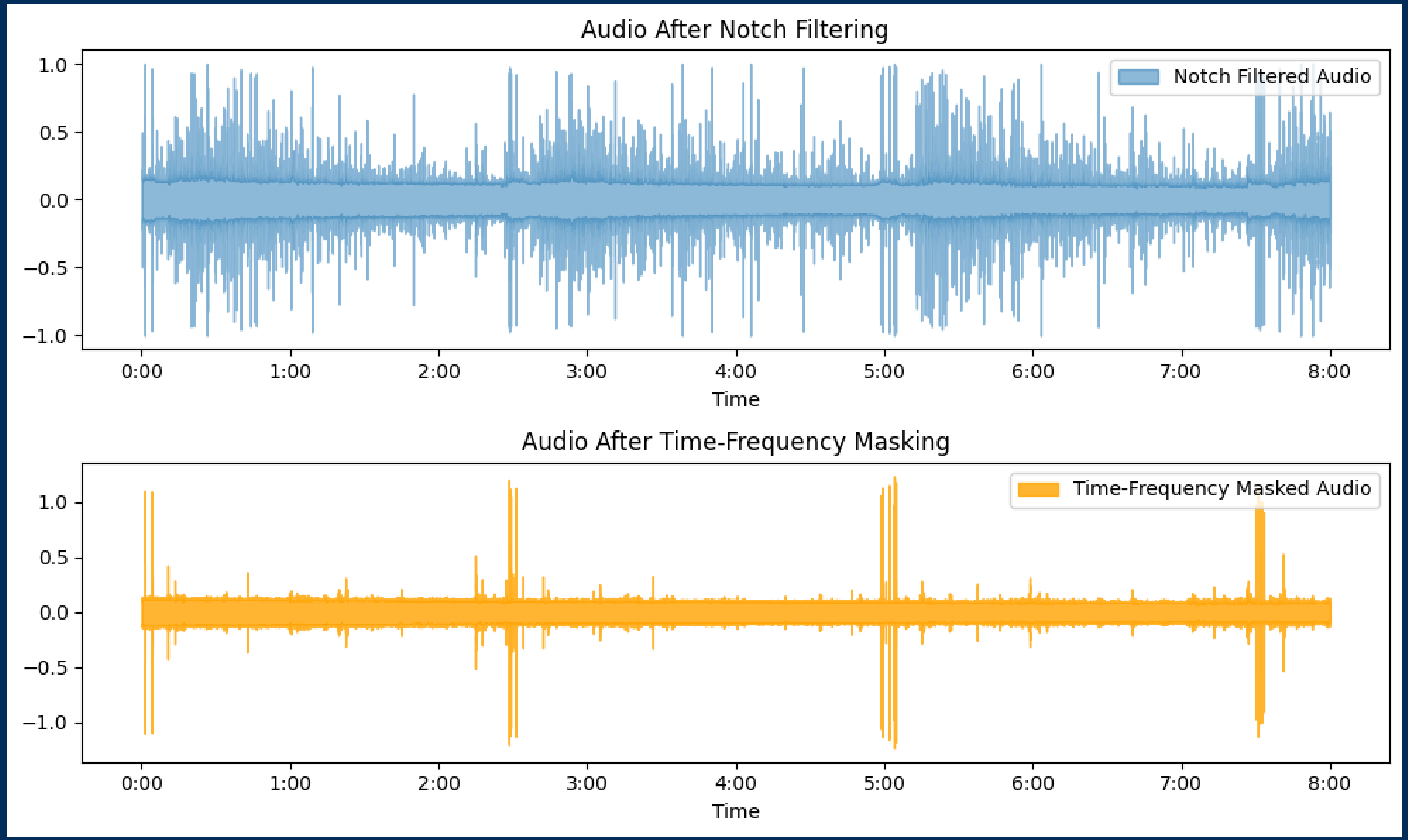
Noise Reduction Results

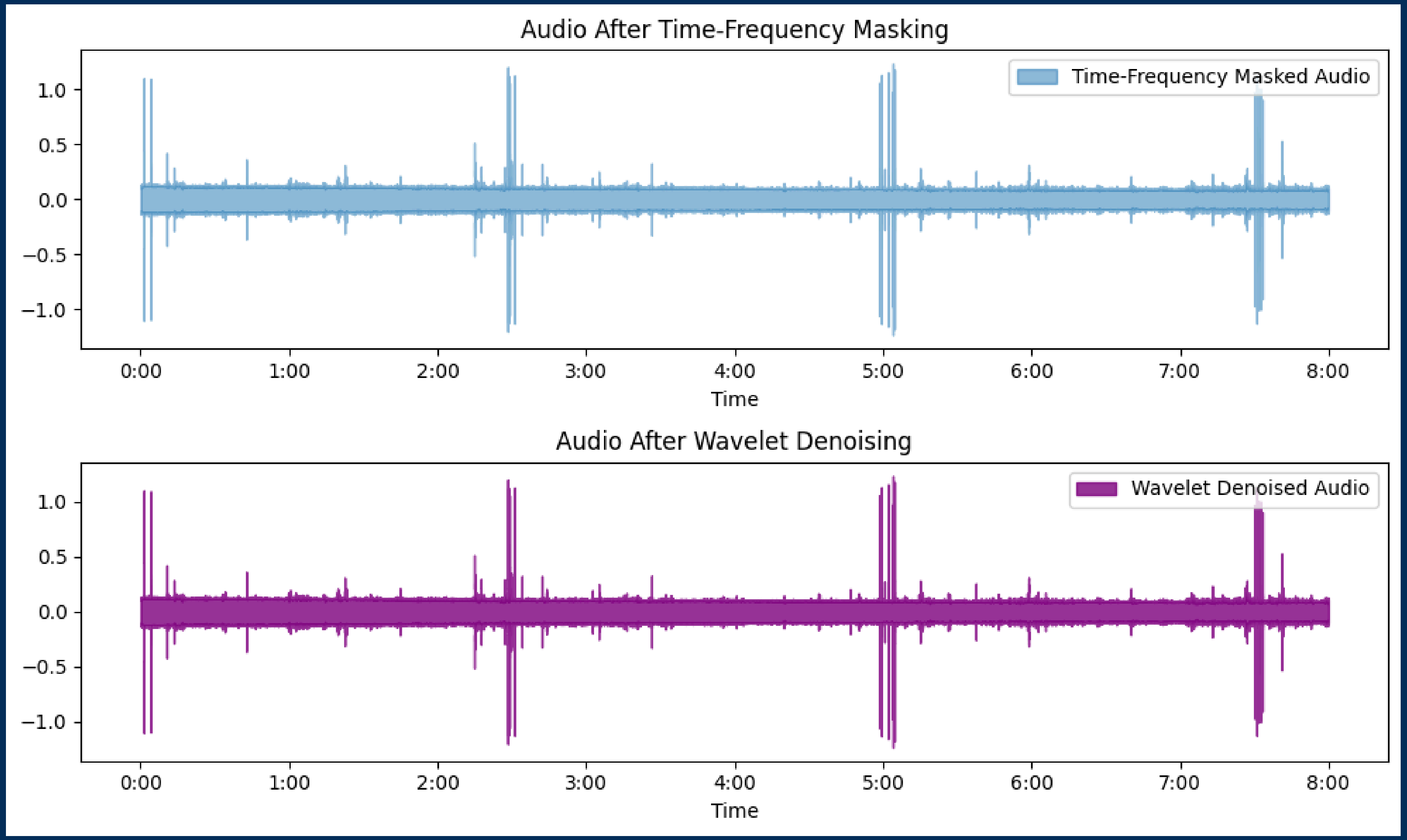
- Methods and Results:
    a. Frequency Band Suppression (Notch Filtering):
        - No difference in static noise.
    b. Time-Frequency Masking:
        - Less static noise is removed, but other surrounding noises/features are completely removed.
    c. Wavelet Transform:
        - No difference in static noise.
    d. Combination of Notch, Time-Frequency Masking, and Wavelet:
        - All noises are removed, including important features, leaving only shrimp snapping sounds.
    e. Spectral Subtraction + Wavelet Denoising:
        - Best result: 80% static noise is removed, and surrounding sounds are retained.
- Inference:
    - Spectral subtraction + wavelet denoising is the most effective method for noise reduction.





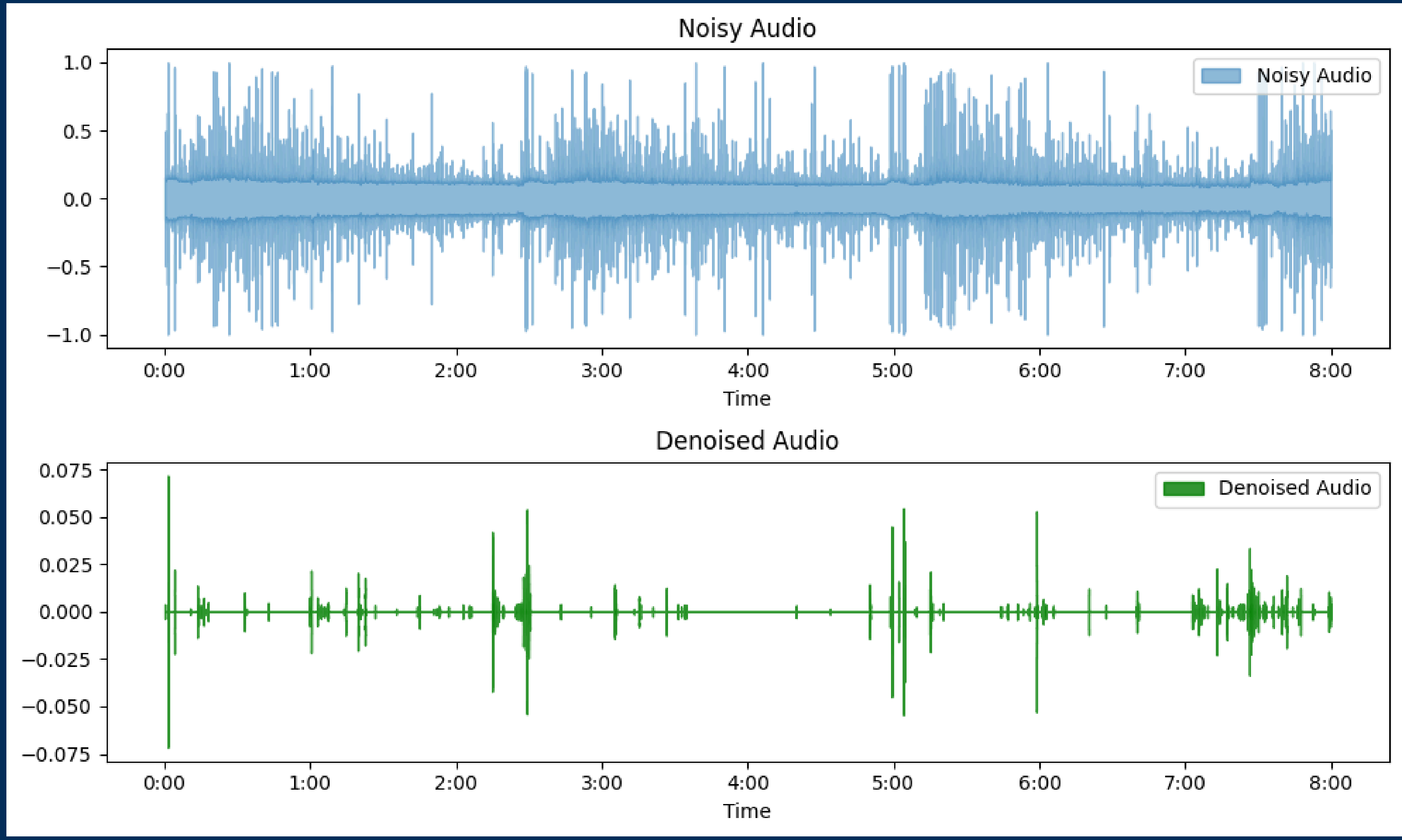
Results and Discussion



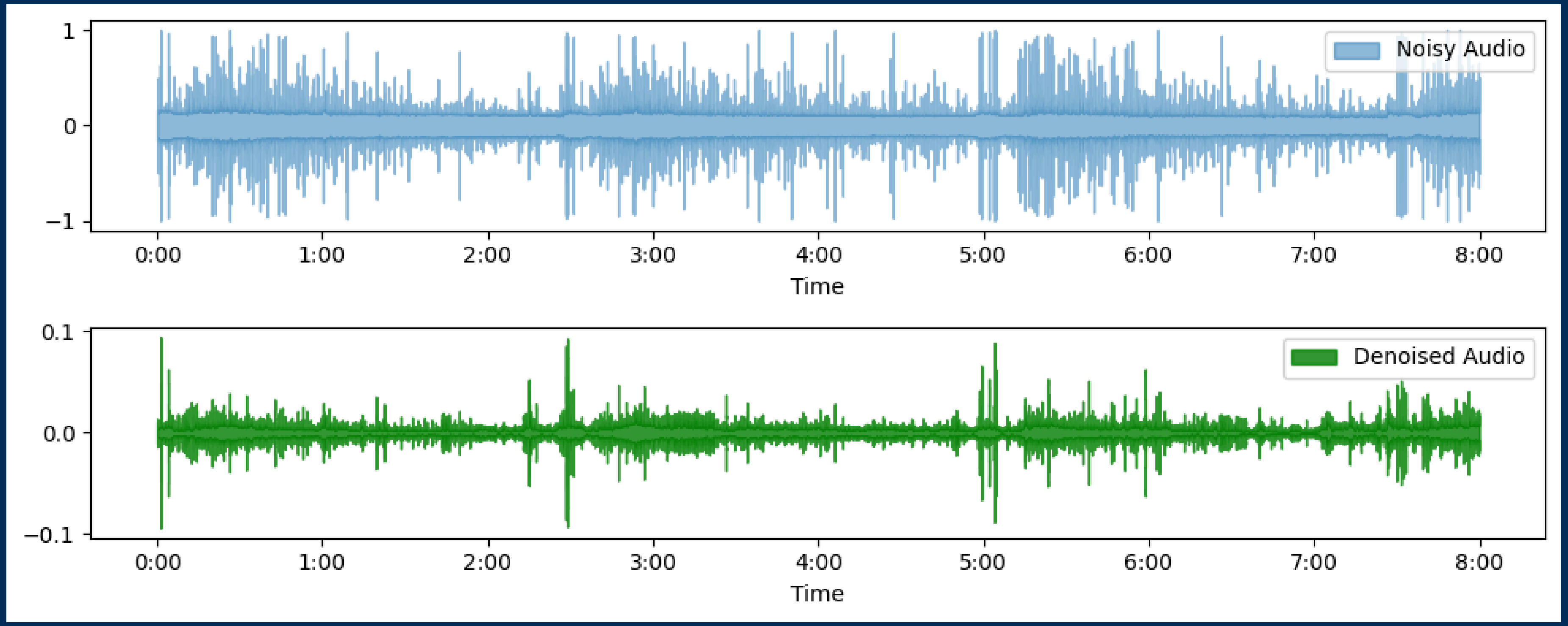


Results and Discussion

All Combined

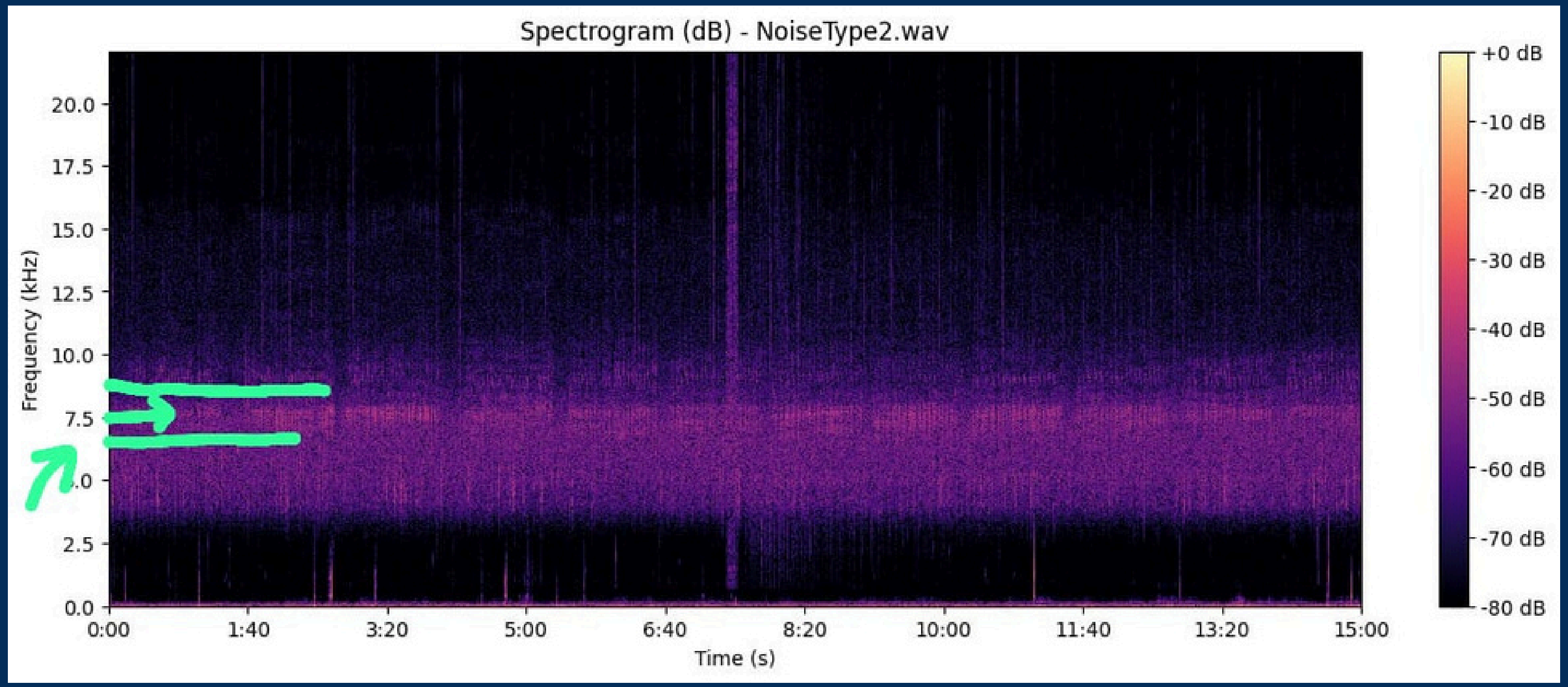


Spectral subtraction + Wavelet denoising

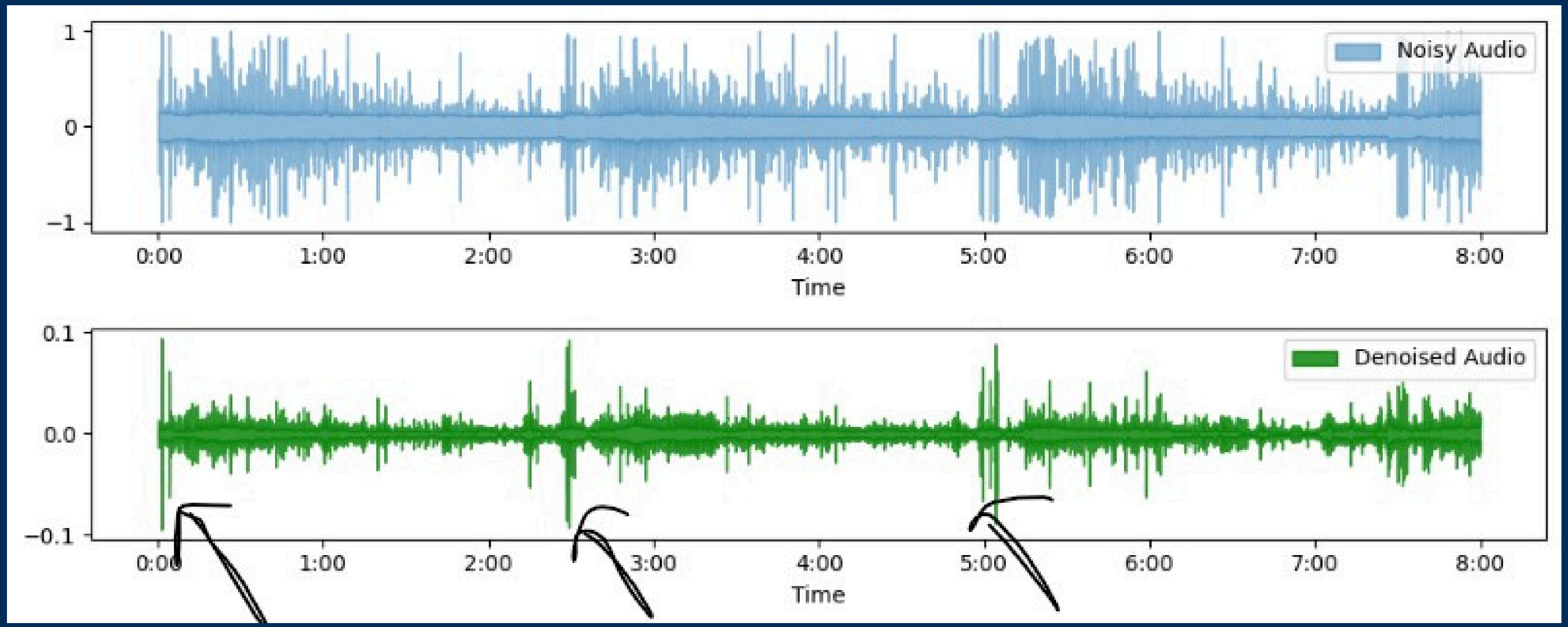


Results and Discussion

Insect Noise Detection



Shrimp Snapping Sounds

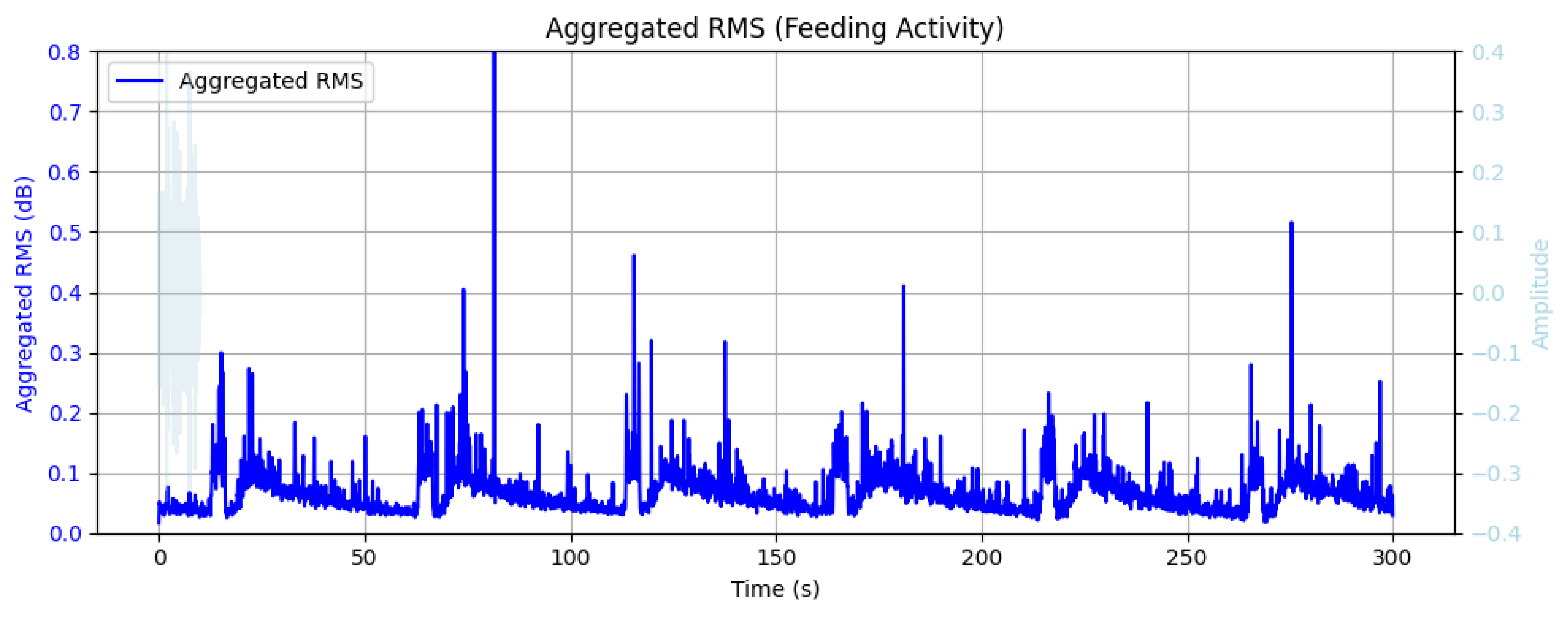


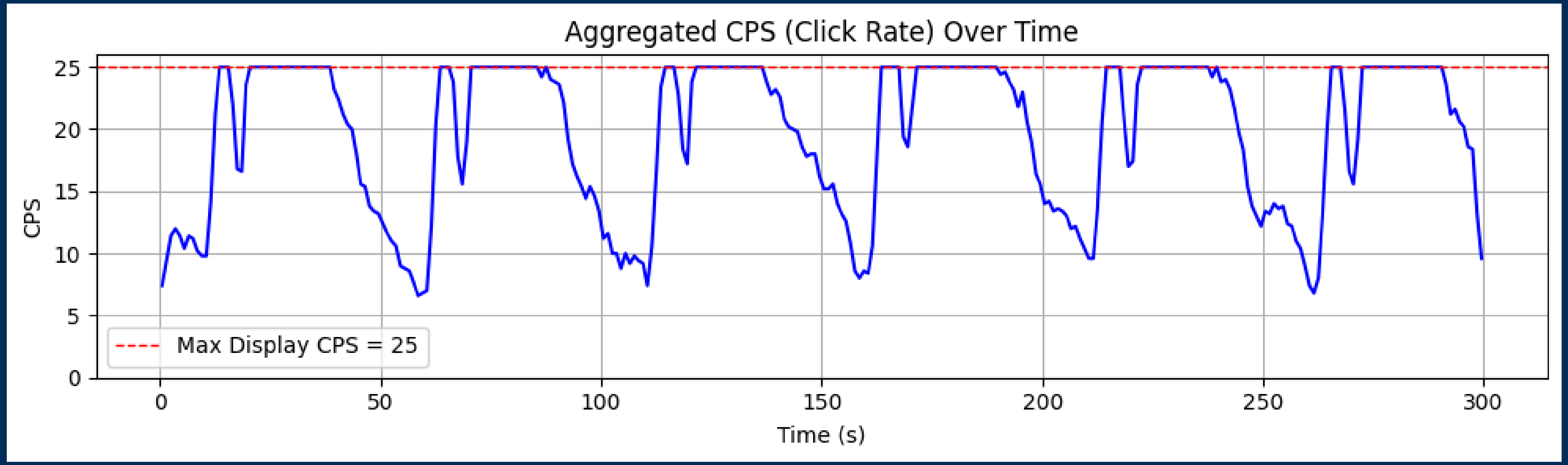
Summary of Key Findings

1. Spectrogram is the most effective tool for detecting insect noise (7.5–8.5 kHz).
2. Waveform, MFCC, and RMS energy are useful for identifying shrimp sounds but not insect noise.
3. Best noise reduction method: Spectral subtraction + wavelet denoising.
4. Insect noise is clearly detectable in NoiseType2 but not in NoiseType1.

Results and Discussion

RMS and CPS Calculation






```
...  Audio duration: 300.00 seconds
     Sampling rate: 44100 Hz

     CPS Values Over Time:
     Time (s)         CPS
     0.50             7.40
     1.50             9.40
     2.50             11.40
     3.50             12.00
     4.50             11.40
     5.50             10.40
     6.50             11.40
     7.50             11.20
     8.50             10.20
     9.50             9.80
     10.50            9.80
     11.50            14.20
     12.50            21.20
     13.50            27.40
     14.50            27.40
     15.50            27.40
     16.50            22.00
     17.50            16.80
     18.50            16.60
     19.50            23.60
     ...
     Maximum CPS: 46.20
     Minimum CPS: 6.60
     Number of frames with CPS >= 5: 300
     Number of frames with CPS >= 10: 272
```

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Conclusion

- Successfully reduced **80% static noise** in NoiseType1 using spectral + wavelet.
- Confirmed **shrimp snapping** and feeding sounds isolatable from noise.
- Identified **distinct insect noise pattern** in NoiseType2 spectrogram.
- NoNoise **benchmark achieved partially**; NoiseType1 insect presence unclear.
- Progress toward **robust shrimp feeding** behavior analysis in noisy audio.

LIMITATION AND FUTURE WORK

01

Limitation 1

Static noise obscures subtle signals in NoiseType1.

02

Limitation 2

Limited audio samples restrict pattern confirmation.

03

Future Work 2

Expand dataset for accurate frequency mapping.

04

Future Work 1

Use machine learning for sound classification.

Snapshot of Guide Approval

CSE1908 - Capstone Project - Final Review

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to suganya.g

Hello ma'am,

Shrimp feeding behaviour analysis in complex aquatic audio environments Final Project Review 3 PPT and Report as per guidelines given are attached. Please check and approve it maam.

Nithin Kodipyaka
20MIA1075

2 Attachments • Scanned by Gmail

Capstone Rev3 2...

Capstone Report ...

Suganya G
to me

Approved

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THANK YOU!

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