Safety-enabled Active Noise Cancellation Headphones

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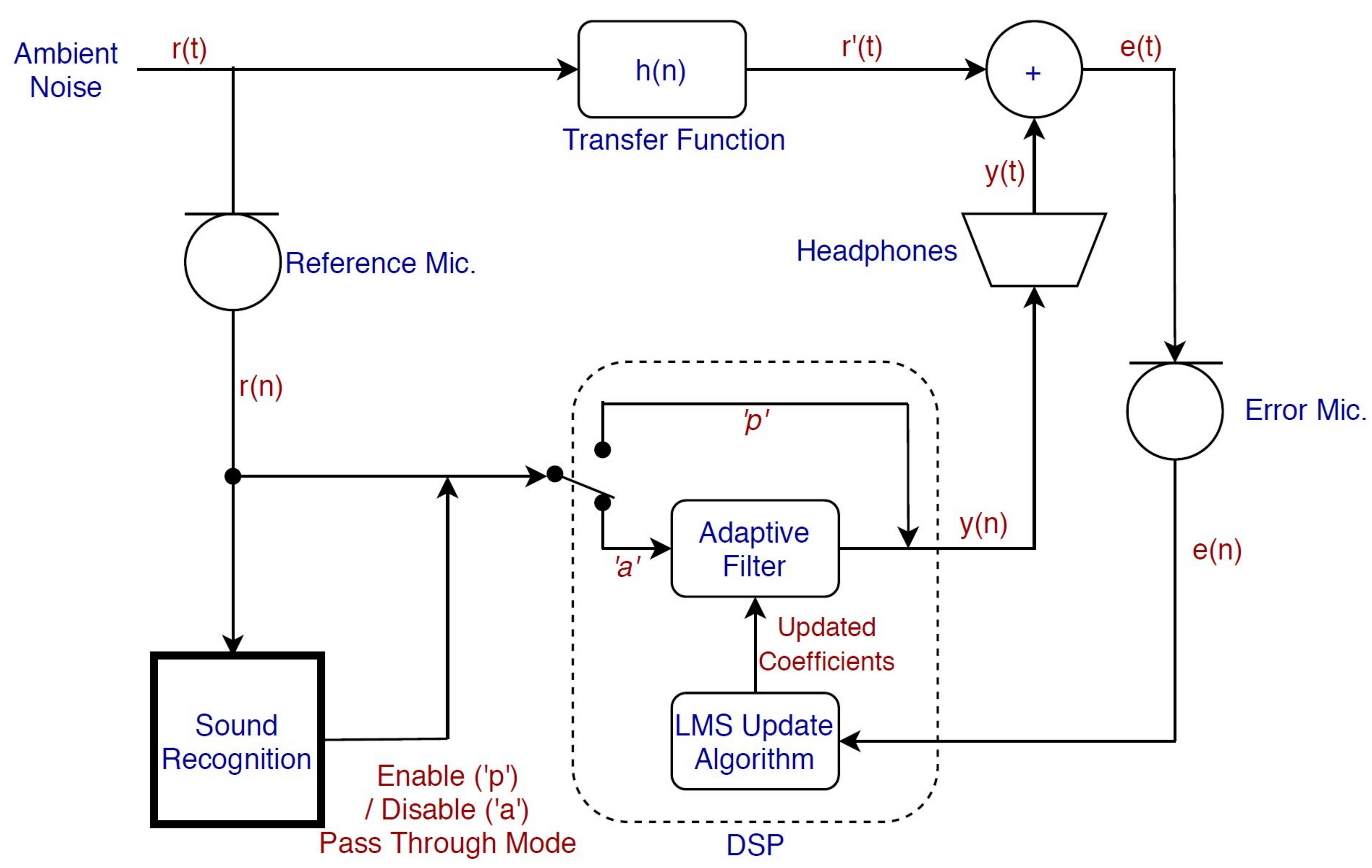
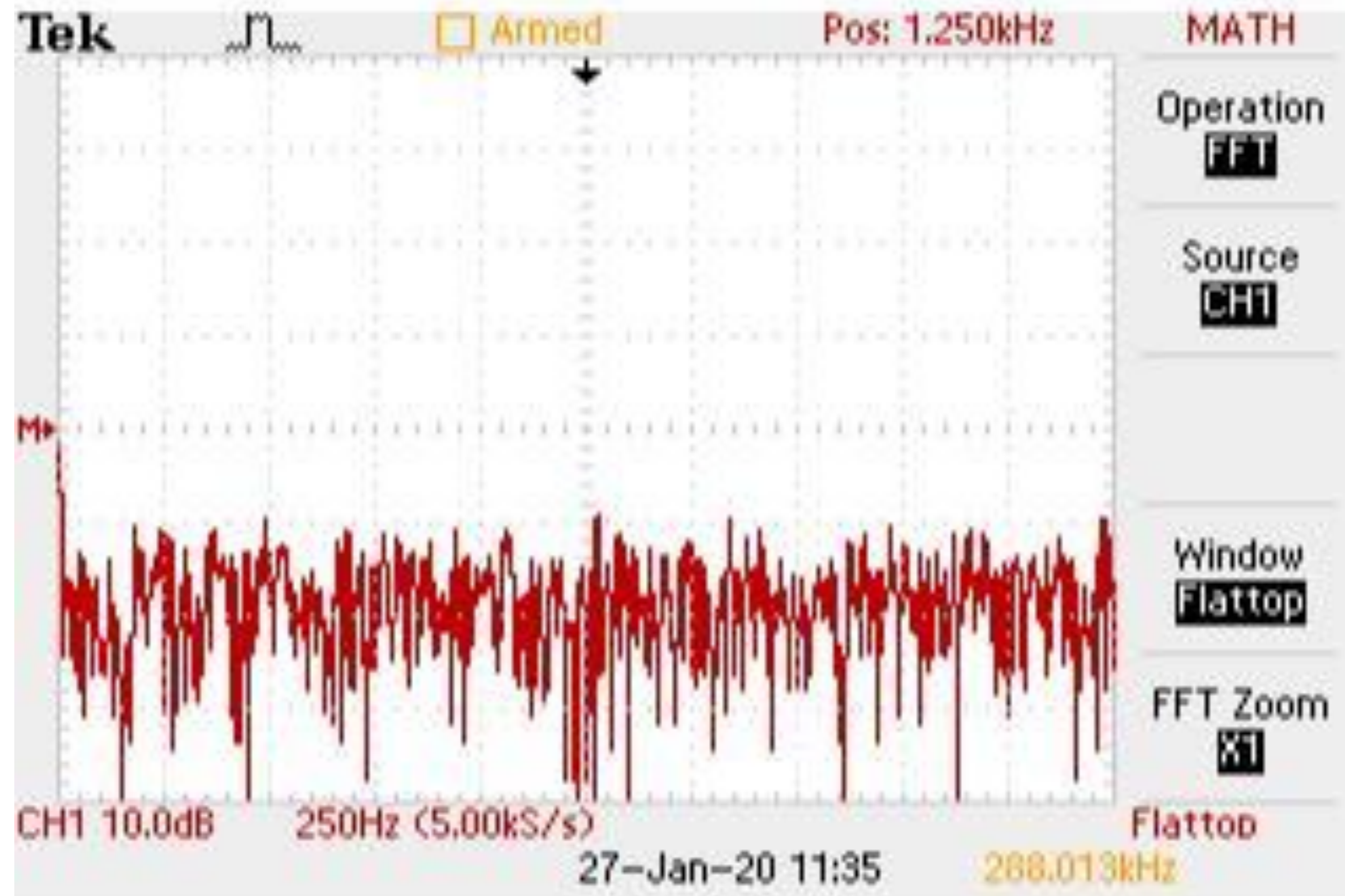
ACTIVE NOISE CANCELLATION TEST RESULTS

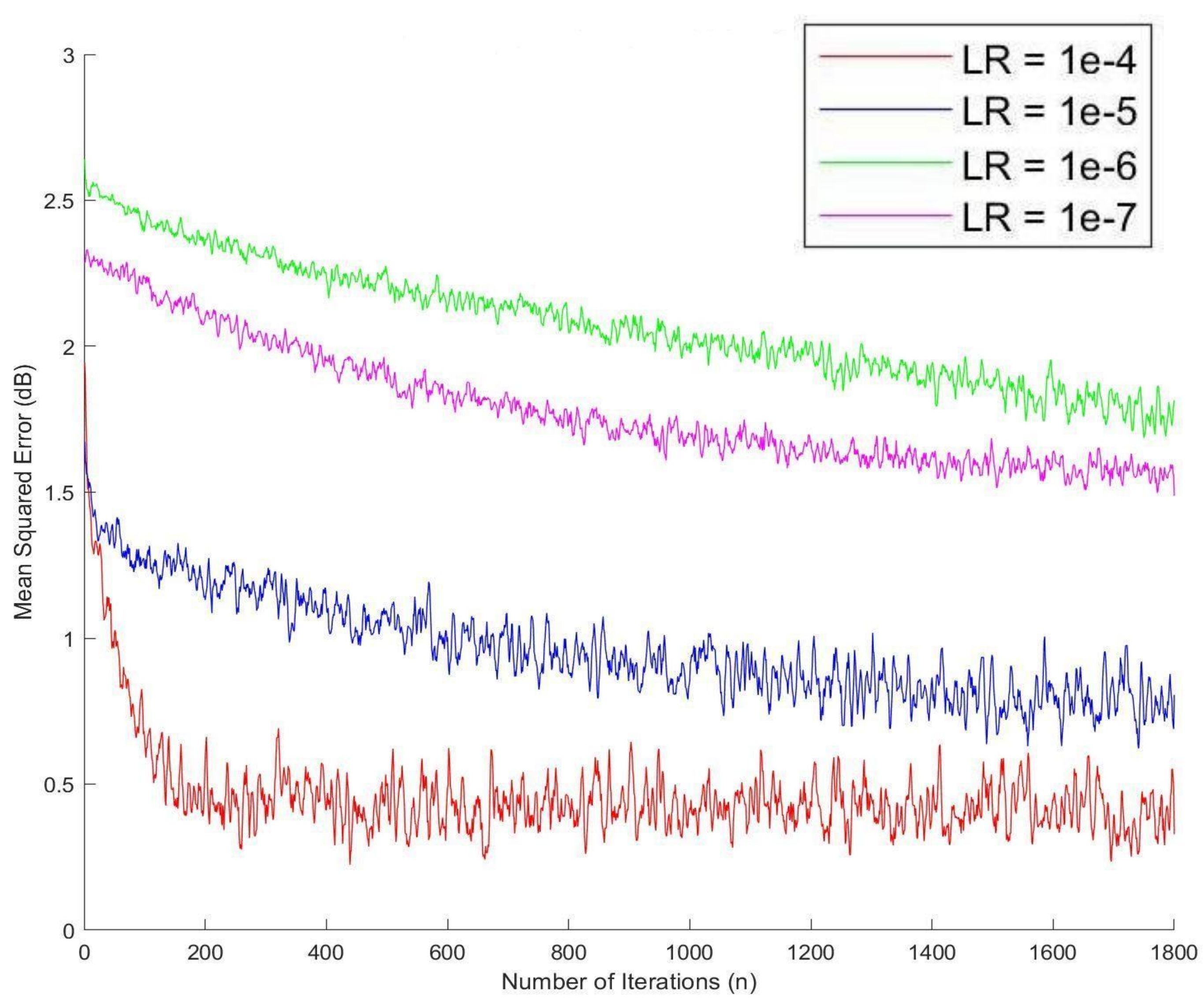
Hardware and Software Configuration



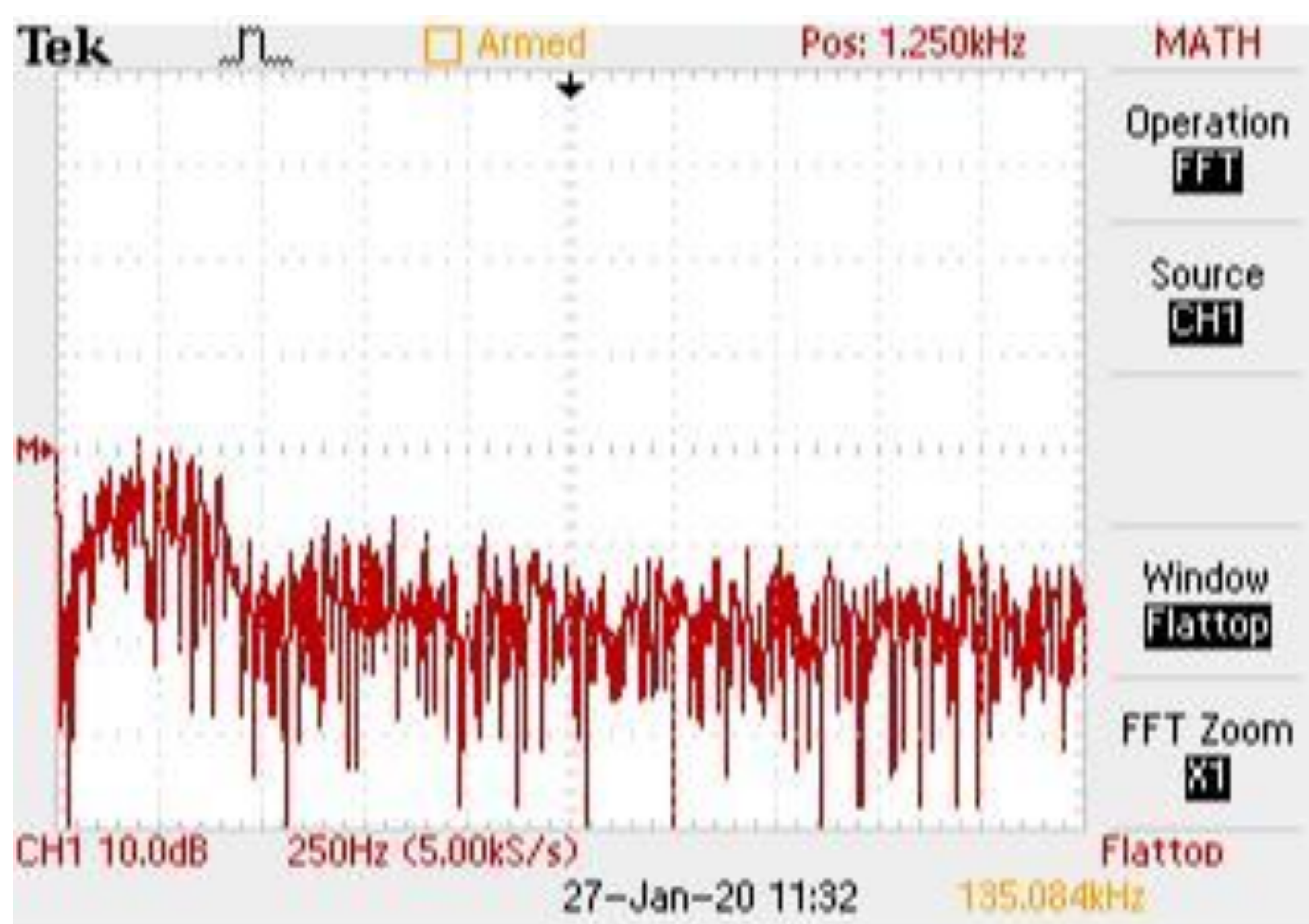
NLMS Filter Output High Noise Floor



Learning Curve for LMS Adaptive Filter



Passthrough Output High Noise Floor



SOUND RECOGNITION TEST RESULTS

Sound Recognition Accuracy WRT Speech Levels vs. Ambient Noise Levels

		Speech Volume Level		
Ambient Noise Type		65dB	75dB	85dB
Background	30dB	69%	75%	93%
Airplane Noise	60dB	63%	68%	74%
Airplane Noise	75dB	>5%	58%	65%
City Noise	60dB	59%	66%	73%
City Noise	75dB	>5%	56%	64%

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INTRODUCTION

Motivation: Existing Active Noise Control (ANC) solutions now cancel noise to such a high degree, important environmental cues, such as a user's name or warning signals, are being filtered out. The removal of these cues poses as an inconvenience to the user, and at times a safety risk as well.

Objectives: Develop an ANC platform on a TI C6748 Digital Signal Processor

Develop a sound recognition platform to identify environmental cues

Challenges:

- Implementing simulated algorithms into an embedded system
- Interfacing microphones and speakers in a real-world setting
- Designing and optimizing an LMS algorithm
- Ensuring proper sound recognition through inherently noisy settings

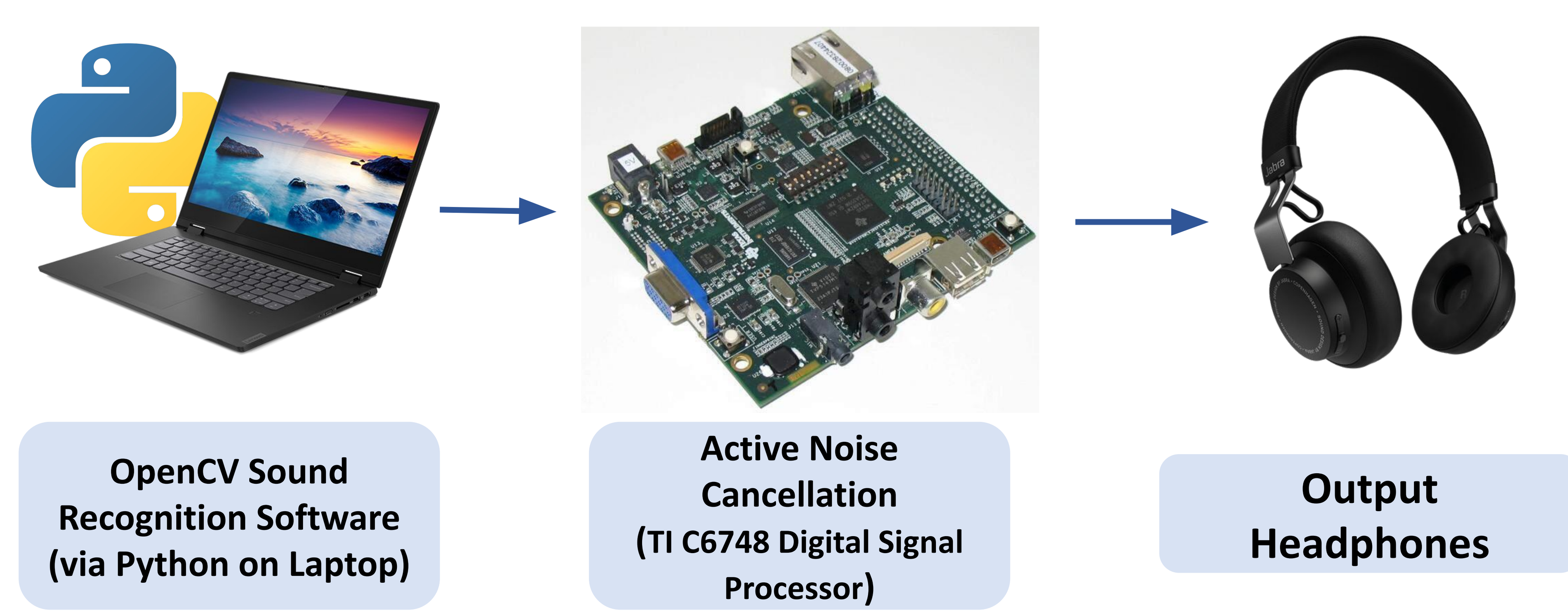
ANALYSIS

- **LMS vs. NLMS**: As opposed to the fixed step size of the LMS filter, the normalized LMS filter step size is dependent on previous inputs, resulting in a system that is less sensitive to large fluctuations in input signal power. [1]
- **Effective attenuation bandwidth and sampling rate**: Appropriate sampling rate selection is needed to avoid introducing frequency content that is outside of the desired attenuation bandwidth.
- **Tradeoff between filter taps and sampling rate:** The number of filter taps used to estimate the primary path is limited by the input sampling rate.
- **DSP selection:** MIPS, ADC/DAC resolution, sampling rate, frequency response.
- **Offline vs. online ML speech-to-text model:** Pocket sphinx, a fast and lightweight offline model, was found to be 28% less accurate than the online Google Speech Recognition model. [2]
- **Sound Recognition and Ambient Noise:** The voice recognition worked optimally under low noise environments (63%-93% Accuracy), and adequately when the speech exceeded the levels of the background environment (~71% Accurate).

CONCLUSIONS AND RECCOMENDATIONS

Conclusions:

- Performing digital signal processing on a real-time platform requires multiple domains of knowledge: An understanding of adaptive filtering techniques and embedded hardware engineering.
- Creating a speech recognition model that is robust against ambient noise levels is a necessary step to creating a more functional product.
- Designing a custom solution that optimizes the sensors (microphones), actuators (speakers), and DSP platform together would avoid many integration problems experienced in this project
- Creating a more accurate acoustic model of the ANC system and performing more simulations before implementing the hardware solution would have decrease uncertainty and quickened development



Recommendations:

- Obtain a DSP with a faster input ADC to output DAC conversion rate.
- Purchase microphones with greater sensitivity to pick up more ambient noise. Also research to find proper microphone placement.
- Develop a quicker ML speech-to-text model with equivalent accuracy to Google's

REFERENCES

[1]https://www.cs.tut.fi/~tabus/course/ASP/SGN2206LectureNew5.pdf

[2]https://www.researchgate.net/publication/314938892_Comparing_Speech_Recognition_Systems_Microsoft_API_Google_API_And_CMU_Sphinx

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