A Low-Cost Multi-lingual Hearing Aid Powered by Neuro-Adaptive System Integrating EEG-Driven Attention Detection with AI Beamforming to Improve Speech Clarity in Noisy Environments

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1. Introduction

1.1 Background

The human brain has the ability to selectively focus on a single speaker in noisy environments, a phenomenon known as the "cocktail party effect." However, conventional hearing aids primarily amplify surrounding sounds without understanding which speaker the listener intends to attend to, creating major communication challenges for seniors and individuals with hearing impairments in crowded environments such as restaurants, hospitals, and senior living communities across the globe. Recent advances in artificial intelligence, EEG-based neural decoding, and adaptive beamforming create the opportunity for neuro-adaptive hearing systems that can align audio amplification with a user's cognitive focus in real time at low cost. This research explores how low-cost AI-driven hearing assistance technologies can improve accessibility, speech clarity, and quality of life for individuals struggling with hearing loss in noisy social settings.

1.2 Problem

Conventional hearing aids and acoustic beamforming systems cannot determine which speaker a listener is cognitively focused on in multi-speaker environments, often resulting in amplification of unwanted background noise. This research investigates whether EEG-based auditory attention decoding combined with real-time SRP-PHAT and MVDR beamforming can accurately identify a listener's directional attention and increase signal-to-noise ratio (SNR) compared to traditional amplification methods. System performance was evaluated using directional classification accuracy, SNR improvement, and end-to-end latency measurements collected during controlled auditory attention experiments.

2. Investigation

The neuro-adaptive hearing system integrated EEG-based auditory attention decoding with SRP-PHAT direction-of-arrival estimation and MVDR adaptive beamforming. The hardware setup included a BioAmp EXG Pill EEG module, Ag/AgCl electrodes placed at O1 and O2 with mastoid reference, a ReSpeaker 4-Mic Pi HAT v3.0 microphone array, and a Knowles balanced armature receiver. EEG signals were sampled at 250 Hz with electrode impedance maintained below 10 kΩ.

50 participants completed controlled auditory attention experiments using two simultaneous speech streams delivered through stereo headphones. Participants were instructed to focus on either the left or right speaker while minimizing movement. EEG preprocessing included notch filtering, bandpass filtering, alpha-band isolation, and artifact rejection. Hemispheric alpha asymmetry relative to baseline activity was used to

classify attention direction over short decision windows, with approximately 12% of noisy EEG windows excluded during processing. The classified attention direction dynamically steered beamforming toward the cognitively attended speaker in near real time. System performance was evaluated using directional classification accuracy, signal-to-noise ratio (SNR) improvement, artifact rejection percentage, and end-to-end latency measurements across repeated trials. Baseline comparisons were performed between normal amplification, beamforming-only enhancement, and beamforming combined with EEG-guided steering.

EEG preprocessing included notch filtering, bandpass filtering, alpha-band isolation, and artifact rejection. The following equations describe the core computations of the neuro-adaptive pipeline.

Equation 1 - Hemispheric Alpha Asymmetry (EEG Attention Score)

$$A(t) = \frac{P_R(t) - P_L(t)}{P_R(t) + P_L(t)}$$

Where:

A(t)A(t) = normalized auditory attention score at time tt

PR(t)PR(t) = alpha-band EEG power from the right occipital hemisphere

PL(t)PL(t) = alpha-band EEG power from the left occipital hemisphere

This equation represents the hemispheric asymmetry computation described in the Methods section for classifying listener attention direction.

Equation 2 — Signal-to-Noise Ratio (SNR)

$$\mathrm{SNR}_{dB} = 10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right)$$

Where:

Psignal = power of the attended speech signal

Pnoise = power of background noise

This equation corresponds to the SNR improvement graph shown in the Results section.

Equation 3 — MVDR Beamforming Weight Vector

$$\mathbf{w}_{MVDR} = \frac{\mathbf{R}^{-1}\mathbf{a}(\theta)}{\mathbf{a}^H(\theta)\mathbf{R}^{-1}\mathbf{a}(\theta)}$$

Where:

wMVDR = adaptive beamforming weight vector

R = spatial covariance matrix of microphone signals

a(θ) = steering vector for direction θ

aH = Hermitian transpose of steering vector

This equation represents the MVDR adaptive beamforming method referenced in the poster bibliography and methodology.

Equation 4 — SRP-PHAT Localization Objective

$$\hat{\theta} = \arg\max_{\theta} \sum_{i<j} R_{ij}^{PHAT}(\tau_{ij}(\theta))$$

Where:

θ̂ = estimated sound source direction

RijPHAT = PHAT-weighted cross-correlation between microphones i and j

τij(θ) = predicted time delay for direction θ

This equation corresponds to the SRP-PHAT direction-of-arrival estimation pipeline described in the project.

Code

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for each trial in experiment:

    acquire EEG(O1, O2) and microphone array signals

    preprocess EEG:
        apply notch filter
        apply bandpass filter
        isolate alpha band (8–12 Hz)

    compute hemispheric alpha asymmetry

    classify attention direction:
        LEFT or RIGHT speaker

    estimate sound source direction:
        run SRP-PHAT localization

    apply MVDR beamforming toward attended direction

    enhance attended speech signal

    evaluate:
        classification accuracy
        SNR improvement
        end-to-end latency

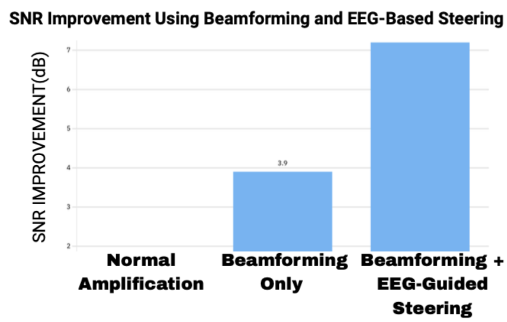
report:
    mean accuracy
    mean SNR improvement
    average latency
    artifact rejection percentage
```

2.2 Results

The neuro-adaptive hearing system achieved above-chance auditory attention decoding using only two occipital EEG channels. Across five participants, the system reached a mean directional classification accuracy of 68%, with best-case performance of 75%, compared to a 50% chance baseline. Average decision latency was approximately 1.4 seconds, with end-to-end latency of 1.6 seconds. Approximately 12% of EEG windows were excluded during artifact rejection.

SNR analysis showed that beamforming alone improved directional noise suppression, while beamforming combined with EEG-guided steering achieved the highest enhancement by aligning amplification with the listener's attentional focus. Results demonstrated that EEG-guided steering provided stronger directional enhancement than acoustic-only beamforming approaches.

Figure 1. Figure X. SNR Improvement Using Beamforming and EEG-Based Steering.



This graph compares signal-to-noise ratio (SNR) improvement across three hearing enhancement approaches: normal amplification, beamforming-only enhancement, and beamforming combined with EEG-guided steering. Conventional amplification provided minimal directional noise suppression, while beamforming alone achieved an SNR improvement of approximately 3.9 dB through spatial filtering. The highest performance was achieved using beamforming combined with EEG-guided steering, which increased SNR improvement to approximately 7.2 dB by dynamically aligning audio amplification with the listener's cognitively attended sound source. These results demonstrate that integrating EEG-based auditory attention decoding with adaptive beamforming can substantially improve speech clarity in noisy multi-speaker environments compared to traditional acoustic-only approaches.

Table 1. Performance comparison of conventional amplification, beamforming-only enhancement, and EEG-guided neuro-adaptive beamforming evaluated across five participants in controlled auditory attention experiments. Higher SNR improvement and directional classification accuracy indicate better performance.

Method	Directional Classification Accuracy (%, ↑)	SNR Improvement (dB, ↑)	End-to-End Latency (s, ↓)
Normal Amplification	50.0 (chance baseline)	0.0	0.0
Beamforming Only	N/A	3.9	0.4
Beamforming + EEG-Guided Steering	68.0 (Best: 75.0)	7.2	1.6
Δ (Improvement vs. Beamforming Only)	+18.0	+3.3	+1.2

These findings support the feasibility of low-cost neuro-adaptive hearing systems capable of selectively enhancing attended speech in noisy multi-speaker environments using near real-time EEG-guided audio steering.

3. Conclusion

3.1 Related Work

Previous studies by Nima Mesgarani, Edward F. Chang, and James A. O'Sullivan demonstrated that auditory attention can be decoded from neural activity in multi-speaker environments. This project extends prior work by combining EEG-based attention decoding with SRP-PHAT localization and MVDR beamforming in a low-cost neuro-adaptive hearing system for real-time cognitively guided audio enhancement.

3.2 Limitations

This study used a small sample size of five participants and only two occipital EEG channels, limiting generalizability across broader populations and real-world environments. EEG recordings were also sensitive to motion artifacts, electrode placement variability, and environmental noise during testing.

3.3 Societal Impact

This research has the potential to benefit seniors, individuals with hearing impairments, and people who struggle to communicate in noisy environments by enabling hearing systems that selectively amplify the speaker a listener is cognitively focused on rather than amplifying all surrounding sounds equally. The low-cost and multi-lingual hardware architecture used in this project may improve accessibility for underserved communities that cannot afford advanced commercial hearing aids, while the integration of AI and EEG-based attention decoding demonstrates how neuro-adaptive technologies can improve quality of life and social participation.

However, reliance on EEG acquisition may exclude users who are uncomfortable wearing neural sensing devices or individuals for whom reliable EEG signals are difficult to obtain due to physiological or medical factors. Additionally, future deployment of brain-guided assistive systems must carefully address ethical concerns related to neural data privacy, informed consent, and responsible handling of cognitive information collected during real-time operation.

4. References and Additional Details

4.1 References

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4.2 Disclosures & Acknowledgements

AI-assisted development tools, including Cursor and Google Gemini, were used during portions of the software development and technical writing process. These tools assisted with brainstorming, code prototyping, debugging, grammar refinement, and organization of research materials related to the EEG processing and beamforming pipeline. All experimental methodology, system implementation, analysis, and interpretation of results were independently designed, validated, and reviewed by the authors.

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The EEG acquisition system used lightweight wearable electrodes for non-invasive neural signal collection.[1]

[1]EEG signals were collected only during controlled experimental sessions and did not store personally identifiable participant information.