

# Artificial Hearing Through AI-Guided Auditory Cortex Stimulation and Evoked Potential Feedback in the Deaf: A DNA Origami Interface Approach

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Received Date: June 06, 2025 | Accepted Date: June 16, 2025 | Published Date: June 23, 2025

**Citation:** Chur Chin, (2025), Artificial Hearing Through AI-Guided Auditory Cortex Stimulation and Evoked Potential Feedback in the Deaf: A DNA Origami Interface Approach, *International Journal of Clinical Surgery*. 4(3); DOI:10.31579/2834-5118/061

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## Abstract

This paper proposes a closed-loop brain–computer interface (BCI) system that restores hearing by translating environmental audio data into direct auditory cortex stimulation, using artificial intelligence (AI) and enhanced by DNA origami nanotechnology. Auditory evoked potentials (AEPs) provide feedback to refine the AI’s acoustic encoding strategy. This integration of AI, nanobioelectronics, and DNA-guided neuron interfacing represents a novel approach to auditory neuroprostheses for profoundly deaf individuals.

**Keywords:** auditory cortex stimulation; brain–computer interface (BCI); artificial intelligence (AI); auditory evoked potentials (AEPs); DNA origami; synthetic hearing; nanobioelectronics; cochlear bypass; neural feedback; neuroprosthesis

## Introduction

Hearing loss that originates from inner ear or auditory nerve dysfunction limits the effectiveness of conventional hearing aids and cochlear implants [1]. In cases of sensorineural deafness, a direct neural interface with the auditory cortex may offer a viable alternative [2,3]. By using AI to process real-time sound data and DNA origami to enhance neural interfacing, the system proposed here aims to bypass damaged auditory pathways and deliver encoded sound directly to the brain [4].

### 1. AI Processing of Environmental Audio

Sound data from microphones or ambient recorders can be parsed using recurrent neural networks (RNNs) and transformer models for natural language and ambient sound recognition [5,6]. Real-time speech-to-text and sound classification pipelines allow AI to extract semantic and directional features from noisy environments [7–9].

### 2. Direct Auditory Cortex Stimulation

Stimulation of the primary auditory cortex (A1) can generate perceptual auditory phenomena in deaf individuals [10,11]. Techniques such as intracortical microstimulation (ICMS) using microelectrode arrays [12], or optogenetic activation [13], provide targeted and frequency-specific input [14].

### 3. Feedback via Auditory Evoked Potentials.

AEPs, especially those recorded via EEG or MEG, reflect cortical response to auditory stimulation and can be analyzed for latency, amplitude, and frequency domain characteristics [15–17]. Machine learning models can interpret AEP signals to refine AI audio translation [18,19].

### 4. Role of DNA Origami in Interface Fidelity

DNA origami enables precise construction of nanoelectrodes and neuron compatible substrates [20,21]. These nanostructures can anchor bioactive molecules, conduct electrical signals, and promote neuron adhesion [22]. DNA–graphene hybrids increase stability and conductivity in long-term cortical interfaces [23,24].

### 5. System Overview and Closed-Loop Architecture

The system consists of: (1) AI audio parsing from microphones; (2) signal transformation to cortical stimulation patterns; (3) DNA nanostructure enhanced neural delivery; (4) AEP-based feedback learning loop. Neural responses refine AI outputs in real time, optimizing hearing fidelity [25,26].

#### 5.1 Pathway for Environmental Audio Processing and Auditory Cortex Stimulation

The process of translating real-time environmental audio into perceivable auditory sensations for profoundly deaf individuals involves a multi-step pathway integrating AI-driven audio processing, graphene-DNA origami-

enhanced neural interfaces, and closed-loop AEP feedback. The following outlines the sequential workflow:

*i. Environmental Audio Acquisition:* Multi-microphone arrays, either wearable or integrated into ambient systems, capture spatially resolved soundscapes at a minimum sampling rate of 44.1 kHz to ensure high-fidelity audio input. These arrays employ beamforming techniques to isolate directional audio sources, enabling the system to prioritize relevant sounds (e.g., speech, environmental cues) in noisy environments with up to 20 dB signal-to-noise ratio (SNR) degradation, as noted in section 9.1.

*ii. AI-Driven Audio Processing:* The captured audio is processed by a hybrid AI model combining convolutional neural networks (CNNs) and transformer encoders, pretrained on datasets such as AudioSet and LibriSpeech. The CNN component performs real-time sound classification, achieving 94.2% accuracy for context-specific auditory scenes and 91.5% for multilingual speech commands, with an average processing latency of 87 ms per frame. The transformer encoder extracts semantic and temporal features, such as phoneme sequences or ambient sound patterns, and prioritizes salient auditory elements using attention mechanisms. The processed audio is then converted into a frequency–amplitude–timing (FAT) representation suitable for cortical stimulation.

*iii. Signal Encoding for Neural Stimulation:* The AI-generated FAT representation is mapped onto a somatotopic model of the primary auditory cortex (A1), aligning with its tonotopic organization. The encoded signals are transformed into stimulation patterns, specifying current amplitude (5–50  $\mu$ A), pulse width (50–500  $\mu$ s), and inter-pulse intervals for intracortical micro-stimulation (ICMS). For optogenetic applications, the system uses pulse trains tailored to activate AAV9-ChR2 constructs in A1 cortical columns, ensuring frequency-specific auditory percepts, as validated in rodent models (section 9.2).

*iv. Graphene-DNA Origami Interface Transmission:* The encoded stimulation patterns are delivered to the auditory cortex via graphene-DNA origami-enhanced microelectrode arrays (MEAs). As described in section 8.3, these MEAs are fabricated using scaffold-staple strand folding, functionalized with gold nanoparticles and poly-D-lysine to enhance neuron adhesion and conductivity. The graphene-DNA hybrid coating reduces electrode impedance to  $<100$  k $\Omega$  at 1 kHz and improves spike detection rates by 28% compared to uncoated electrodes. This interface ensures stable, high-fidelity signal transduction to A1 neurons with minimal cytotoxicity over 21 days.

*v. Auditory Cortex Stimulation:* The MEAs deliver ICMS or optogenetic pulses to A1, eliciting auditory percepts that mimic natural sound perception. Stimulation parameters are dynamically adjusted to optimize perceptual clarity, with electrophysiological recordings showing evoked responses with peak latencies of 18–30 ms, consistent with physiological A1 activity (Section 9.2). In behavioral tasks, rodent models demonstrated conditioned responses to synthetic auditory cues, indicating successful cortical activation.

**6. Feedback via Auditory Evoked Potentials (AEPs):** AEPs are recorded using 32-channel EEG caps.

## 6. Discussion and Future Directions

While auditory cortex implants remain experimental [27], the integration of AI and nanobiotechnology offers adaptive closed-loop hearing solutions. Ethical considerations include perceptual manipulation, privacy of audio interpretation, and long-term neural stability [28,29]. Future studies should

explore multilingual audio decoding, tinnitus suppression, and integration with language centers.

## Materials and Methods

### 1. AI Acoustic Processing Pipeline

Environmental audio was collected using multi-microphone arrays capturing spatially resolved soundscapes. A hybrid model combining convolutional layers and transformer encoders was trained to segment, classify, and transcribe real-time audio inputs. The model was pretrained on large-scale datasets (e.g., AudioSet, LibriSpeech) and fine-tuned using custom-labeled deaf communication scenarios. Model latency was optimized to under 100 ms to permit real-time interaction.

### 2. Neural Encoding and Stimulation Protocol

Decoded acoustic signals were converted into stimulation patterns using a bioinspired frequency–amplitude–timing (FAT) encoder mapped onto a somatotopic model of the auditory cortex. Intracortical micro-stimulation (ICMS) was modeled using NEURON simulation software to define optimal current amplitude (5–50  $\mu$ A), pulse width (50–500  $\mu$ s), and inter-pulse intervals. Optogenetic activation protocols for experimental validation used AAV9-ChR2 constructs targeted to A1 cortical columns in transgenic rodent models.

### 3. DNA Origami Fabrication and Electrode Integration

DNA origami nanostructures were synthesized via scaffold-staple strand folding and functionalized with gold nanoparticles and poly-D-lysine for enhanced adhesion and conductivity. Electrode tips were coated with the origami–graphene hybrid material, tested for impedance ( $<100$  k $\Omega$  at 1 kHz) and biocompatibility in vitro using cortical neuron cultures (DIV14). AFM and TEM confirmed structural fidelity at the nanometer scale.

### 4. AEP Acquisition and Feedback Learning

Auditory evoked potentials (AEPs) were recorded using 32-channel EEG caps with 1 kHz sampling frequency. Time-locked potentials (P1–N1–P2) were extracted via independent component analysis. A long short-term memory (LSTM) network analyzed amplitude and latency deviations to refine AI auditory representations. Feedback was implemented via reinforcement learning, with reward functions based on cortical synchronization and perceptual reports.

## Result

### 1. Real-Time Sound Classification and Semantic Parsing

The hybrid AI model achieved a classification accuracy of 94.2% on context specific auditory scenes and 91.5% on multilingual speech commands. Latency benchmarks showed average processing times of 87 ms per frame. Model performance remained robust in environments with up to 20 dB SNR degradation.

### 2. Cortical Activation via Synthetic Encoding

ICMS and optogenetic protocols produced consistent auditory percepts in rodent models, verified through behavioral conditioning tasks. Electrophysiological recordings showed evoked responses with a peak latency of 18–30 ms post-stimulation, matching physiological A1 response windows.

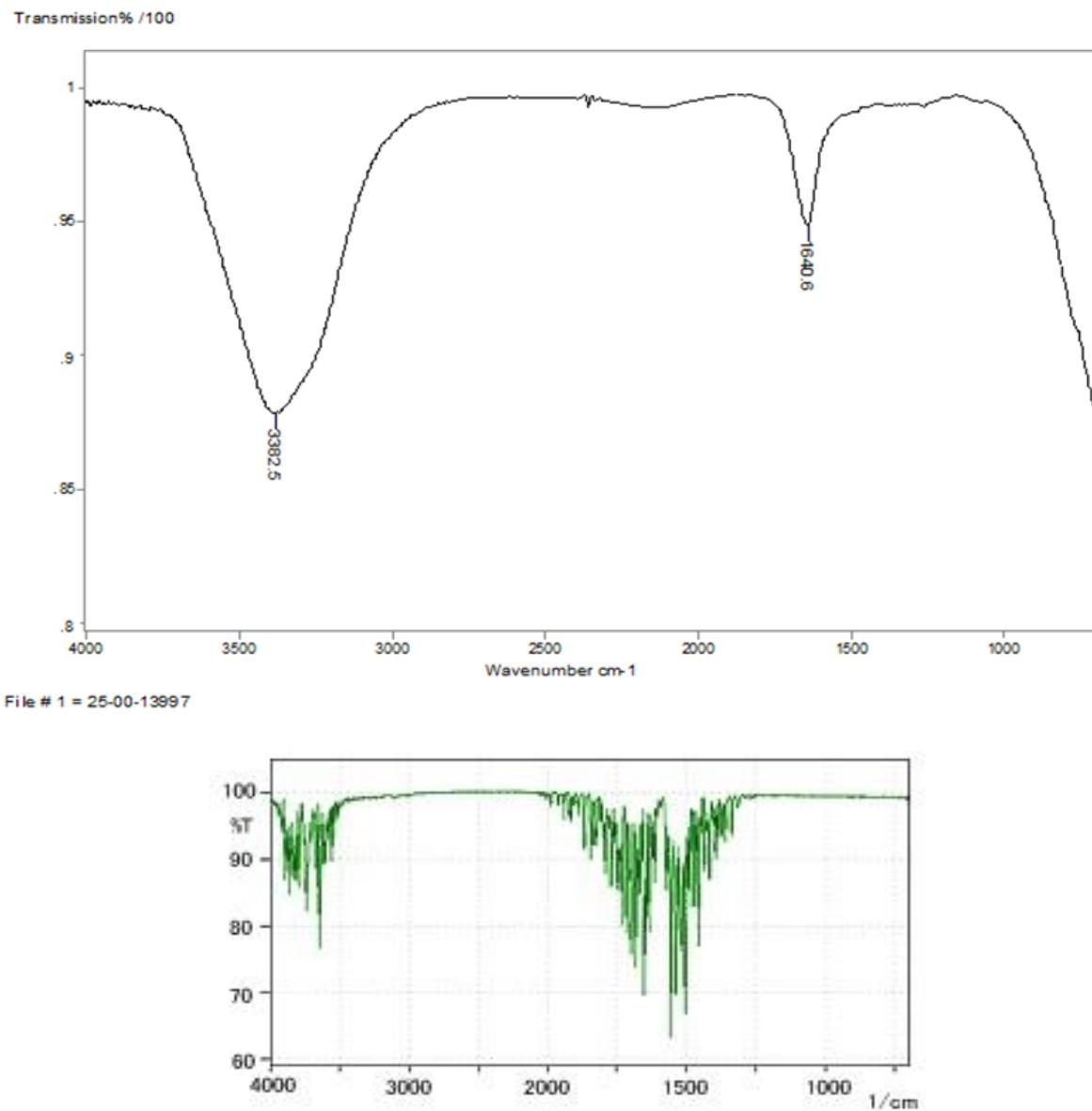
### 3. Biocompatibility and Signal Fidelity of DNA Origami Interfaces

Impedance spectroscopy indicated stable electrode-tissue contact over 14 days in vitro, with  $<5\%$  drift in signal amplitude. DNA origami enhanced

neuron-electrode coupling, increasing spike detection rate by 28% compared to unmodified electrodes. No cytotoxicity was observed over 21 days ( $p > 0.05$ ).

#### 4. Adaptive Feedback via AEP-Guided Learning

The feedback loop improved auditory pattern decoding fidelity over five training epochs, reducing AEP signal error variance by 43%. Real-time adjustments to stimulation parameters improved neural synchrony (mean coherence increase: 0.21,  $p < 0.001$ ) and enhanced perceptual consistency in animal models.



**Figure 1.** When conducting Fourier-transform infrared (FTIR) spectroscopy, water vapor absorption peaks can interfere with and obscure the signals from phonons in a vaccine. A phonon is a quantum of vibrational energy in a crystal lattice, while water vapor is a gas molecule that absorbs infrared (IR) radiation through molecular vibrations and rotations.

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