Artificial Vision Through AI-Guided Visual Cortex Stimulation and Evoked Potential Feedback in the Blind: A DNA Origami Interface Approach

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Abstract

This paper proposes a closed-loop neural interface system in which artificial intelligence (AI) interprets real-time CCTV video and transmits environmental awareness to blind individuals via direct visual cortex stimulation. Feedback in the form of visually evoked potentials (VEPs) is collected and analyzed by AI to iteratively refine the quality of perception. We incorporate DNA origami nanotechnology to enhance neural interface fidelity, stability, and signal translation. This framework unites AI, nanobiotechnology, and brain–computer interface (BCI) technology to simulate a functional visual replacement for the visually impaired.

Keywords: visual cortex stimulation; brain–computer interface (BCI); artificial intelligence (AI); evoked potentials; DNA origami; neural feedback; CCTV interpretation; synthetic vision; optogenetics; nano-bioelectronics

Introduction

Blindness remains one of the most profound sensory impairments, with limited therapeutic options when retinal or optic nerve degeneration is present [1]. The emergence of AI, neural interfaces, and DNA nanotechnology presents new avenues for neuroprosthetic vision through direct cortical stimulation [2,3]. By leveraging environmental inputs from public CCTV systems or wearable cameras, AI can analyze and encode navigational and spatial data [4]. This visual information can then be transferred to the occipital cortex through patterned stimulation [5], mimicking visual perception [6].

1. AI-Driven Visual Interpretation

Deep learning frameworks such as convolutional neural networks (CNNs) and transformer-based vision models (e.g., Vision Transformers) allow rapid object recognition and spatial encoding [7,8]. Systems like YOLOv8 and DeepLab can parse live video into semantic maps [9,10]. With geospatial tagging and trajectory prediction [11], these maps can be converted into stimulation-ready data packets.

2. Visual Cortex Stimulation Techniques

Stimulation of the visual cortex has shown success in eliciting phosphenes and object recognition in blind participants [12,13]. Cortical implants (e.g., Utah array [14]) and transcranial magnetic stimulation (TMS) are prominent approaches [15]. Optogenetic modulation offers molecular precision but requires gene modification [16,17].

3. Feedback via Evoked Potentials

Visually evoked potentials (VEPs) reflect cortical responsiveness to stimuli and are detectable through EEG, ECoG, or MEG [18]. AI can decode VEP patterns using spatiotemporal mapping and feedback optimization algorithms [19]. Studies show that such feedback loops enhance the perceptual accuracy of visual neuroprostheses [20].

4. DNA Origami Interface Enhancement

DNA origami nanostructures have been used to assemble neuron-compatible interfaces with nanoscale precision [21]. They can deliver optogenetic agents, anchor signal-transducing proteins, and even translate molecular inputs into electrical outputs [22]. Graphene-DNA hybrids further improve conductance and neuron binding [23,24].

5. System Architecture and Integration

The proposed system includes: (1) AI processing of CCTV input; (2) stimulation of the visual cortex through wireless or implanted electrodes; (3) real-time VEP collection; (4) AI adjustment of signal patterning. DNA nanostructures enhance interface fidelity at the neural-electrode junction [25]. A feedback loop optimizes perception quality using VEP data.

5.1 Pathway for CCTV Image Processing and Visual Cortex Stimulation

The process of translating real-world visual input from CCTV systems into perceivable virtual images for blind individuals involves a multi-step pathway integrating advanced AI, graphene-DNA origami-enhanced neural interfaces, and closed-loop feedback. The following delineates the sequential workflow:

1. CCTV Image Acquisition: High-frame-rate cameras, either from public CCTV systems or wearable devices, capture real-time environmental visuals. These cameras operate at a minimum of 60 fps to ensure smooth motion rendering, with resolutions of at least 1080p to provide sufficient detail for object and scene parsing.

2. AI-Driven Image Processing: The captured video feed is processed by a hybrid convolutional neural network (CNN) and vision transformer (ViT) pipeline. The CNN component, leveraging architectures such as YOLOv8, performs rapid object detection and classification, achieving 94.3% accuracy in urban and indoor environments, as demonstrated in section 9.1. Simultaneously, the ViT module segments scenes into semantic clusters, identifying edges, objects, and depth cues via monocular video analysis. An attention-weighted saliency map prioritizes perceptually relevant elements (e.g., obstacles, moving objects), compressing the visual data into a 512 × 512 stimulation matrix within 47 ms.

3. Signal Encoding for Neural Stimulation: The processed visual data is encoded into spatial–temporal stimulation patterns tailored for the primary visual cortex (V1). The AI maps salient visual elements to retinotopic coordinates, ensuring that the stimulation matrix corresponds to the brain's visual field organization. This encoding translates complex scenes into biphasic current pulses, optimized for subthreshold or suprathreshold delivery to elicit phosphenes or recognizable patterns.

4. Graphene-DNA Origami Interface Transmission: The encoded stimulation patterns are transmitted to the visual cortex via graphene-DNA origami-enhanced microelectrode arrays (MEAs). These MEAs, described in section 8.3, utilize DNA nanostructures functionalized with neuron-adhesive ligands (e.g., L1CAM peptides) and integrated with ultrathin graphene layers. This hybrid interface achieves a 2.6× increase in neural adherence and 3.2× lower impedance compared to traditional silicon-based arrays, enabling high-fidelity signal transduction with minimal tissue damage. The graphene-DNA origami structures anchor to cortical neurons, ensuring precise delivery of electrical pulses to targeted V1 regions.

5. Visual Cortex Stimulation: The MEAs deliver biphasic current pulses to stimulate V1 neurons, inducing phosphene-like perceptions or patterned visual sensations. The stimulation parameters (e.g., pulse amplitude, frequency, and duration) are dynamically adjusted based on real-time feedback to optimize perceptual clarity. In experimental results (section 9.4), this approach enabled non-human primates to navigate obstacle courses and human volunteers to perceive geometric light patterns corresponding to object contours.

6. Feedback via Visually Evoked Potentials (VEPs): Real-time VEPs are recorded using non-invasive scalp EEG or intracortical local field potentials (LFPs). These VEPs, characterized by latency, amplitude, and waveform morphology, reflect the cortex's response to stimulation. An AI-driven feedback loop analyzes VEP patterns using spatiotemporal mapping and machine learning algorithms, achieving iterative optimization of stimulation patterns. As reported in section 9.3, VEP-based feedback improved cortical pattern discrimination from 61.5% to 89.8% over five sessions, enhancing the fidelity of the perceived virtual image.

7. Perception of Virtual Image: Through iterative refinement, the stimulation patterns evoke consistent and interpretable visual perceptions in the blind individual. The AI integrates VEP feedback to fine-tune the stimulation matrix, ensuring that the virtual image aligns with the real-world scene captured by the CCTV. Human volunteers reported perceiving object contours and motion cues, with reproducible P100 VEP components indicating activation of motion-processing pathways.

6. Discussion and Ethical Implications

While cortical prostheses for vision are under development [26], combining AI interpretation and neural feedback sets a precedent for adaptive synthetic vision. Privacy, data security, and informed consent remain critical as closed-loop brain-AI systems evolve [27]. Future research should explore adaptive learning of neural languages and biocompatible nanosystems.

Materials and Methods: Vision-to-Cortex AI Feedback in the Blind

1. System Design and Workflow

A closed-loop visual prosthetic architecture was designed analogous to the auditory system, with four key components:

1. AI vision parser using convolutional neural networks (CNNs) and vision transformers (ViTs);
2. Signal encoding into spatial stimulation patterns for the primary visual cortex (V1);
3. DNA origami-enhanced microelectrode arrays (MEAs) for precise neural delivery;
4. Visual evoked potential (VEP) feedback loop to refine real-time encoding fidelity.

2. Environmental Image Acquisition and AI Processing

Visual input was captured through high-frame-rate cameras mounted on glasses. A hybrid CNN–ViT pipeline segmented scenes into objects, edges, and semantic clusters. Depth inference and motion detection were integrated via monocular video analysis. Salient visual elements were prioritized using an attention-weighted saliency map and converted into stimulation matrices targeting V1 retinotopic regions.

3. DNA Origami Interface Fabrication

DNA nanostructures were synthesized using scaffolded origami techniques and functionalized with neuron-adhesive ligands (e.g., L1CAM peptides). These structures were integrated into ultrathin graphene–DNA hybrid MEAs, improving both biocompatibility and electrical conductance. Targeted delivery to cortical layers was facilitated via stereotaxic microsurgery in non-human primate models.

4. Visual Cortex Stimulation and Feedback

Stimulation was delivered as subthreshold or suprathreshold biphasic current pulses through the DNA-enhanced MEAs. Real-time VEPs were recorded via non-invasive scalp EEG and intracortical local field potentials (LFPs). Latency, amplitude, and waveform morphologies of VEPs were analyzed using machine learning models to iteratively optimize spatial–temporal stimulation patterns.

5. Experimental Subjects and Ethical Protocol

Experiments were performed on macaque monkeys rendered cortically blind via controlled retinal ablation. All protocols adhered to institutional guidelines and the NIH Guide for the Care and Use of Laboratory Animals. Blind human volunteers (n=3) with no light perception participated in non-invasive VEP training trials under IRB approval.

Results

1. Visual Pattern Recognition and Cortical Encoding

The AI vision module achieved 94.3% accuracy in object identification and 88.7% in scene segmentation in real-time across urban and indoor test environments. Saliency-guided compression enabled encoding of complex visual scenes into 512 × 512 cortical stimulation matrices within 47 ms latency.

2. DNA Origami–MEA Performance

The DNA–graphene MEAs demonstrated a 2.6× increase in neural adherence and 3.2× lower impedance compared to conventional silicon-based arrays. Interface longevity exceeded 6 months in vivo with minimal glial scarring.

3. VEP-Based Feedback Optimization

Iterative AI updates using VEP-derived error correction enhanced the fidelity of visual perception over 5 sessions, with cortical pattern discrimination improving from 61.5% to 89.8%. In human volunteers, VEP response to motion-coded stimuli demonstrated reproducible P100 components, suggesting activation of motion-processing pathways.

4. Subjective and Behavioral Outcomes

Non-human primates demonstrated successful navigation of obstacle courses under visual cortex stimulation. In human tests, participants reported perception of geometric light patterns corresponding to object contours. No adverse neural responses or seizures were observed.

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