Todo list

Visual Cortical Prostheses: Bridging Technology, AI and Human Vision for the Future

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Summary

Visual cortical prostheses represent a revolutionary technology within the field of neuroprosthetics, aimed at restoring vision for individuals with visual impairments through direct neural interfaces. This proposal. . . ABSTRACT WORK IN PROGRESS!!!

Keywords: Visual cortical prostheses, neuroprosthetics, artificial intelligence, phosphene patterns, real-time image processing

Introduction

Globally, blindness affects millions of people, with estimates rising from over 30 million in 2013 to 43.3 million in 2020 (Bourne et al., 2021; Stevens et al., 2013). For certain types of blindness, visual prosthetics present a promising avenue for restoring rudimentary vision through electrical stimulation of the visual system. In the past decade, significant attempts have already been made in early systems that focus on retinal and optic nerve implants, such as the exemplary FDA-approved ARGUSII retinal system by Second Sight Medical (Ho et al., 2015). However, these systems do not provide a solution for individuals who have damage to structures such as the retina or optic nerve in the visual pathway.

Visual cortical prostheses provide a novel approach to stimulating the brain by interface directly with the brain's visual cortex (de Ruyter van Steveninck, van Gestel, et al., 2022). These devices convert visual information from the environment into neural signals that can be processed by the brain.

The core technology involves the generation of phosphenes—perceived spots of light resulting from electrical stimulation of the visual cortex (van der Grinten et al., 2024). However, organizing these phosphenes into coherent and interpretable visual patterns remains a significant challenge.

In order to optimize these phosphene patterns for more accurate representations of a user's surroundings, artificial intelligence (AI) can be leveraged in the form of deep learning algorithms. Algorithms such as Convolutional Neural Networks (CNNs) have already been proven to be effective for image processing of static objects in recent work by de Ruyter van Steveninck, Güçlü, et al. (2022). Deep learning models like CNNs provide a solution to low sampling resolution of complex visual stimuli, enabling the generation of more detailed and accurate reconstruction of the visual scene.

The phosphene simulator described in the article by de Ruyter van Steveninck, Güçlü, et al. (2022) was implemented in Python, utilizing the PyTorch deep learning library for its computational capabilities. It operates by translating electrical stimulation parameters into an estimated phosphene perception, taking into account the history of stimulation to ensure accuracy. The simulator initializes with electrode locations on a flattened cortical map of the primary visual cortex (V1), using the reverse wedge-dipole visuotopic model to map these locations to the user's visual field. This model accounts for the eccentricity and azimuth in the visual field, controlling various parameters to ensure realistic proportions in cortical distance.

To determine the size of the phosphenes, the simulator uses models that estimate current spread from the electrodes, incorporating factors like stimulation current and cortical magnification. The appearance and brightness of phosphenes are modeled with a sigmoidal activation function, taking into account the activation threshold, which introduces variability between electrodes. Temporal dynamics are managed through a memory trace that adjusts phosphene brightness based on stimulation history, incorporating decay and input effects to simulate accommodation. Each frame, the simulator processes stimulation parameters, estimates phosphene characteristics, and renders these effects on a visual field map, summing them to produce the final simulated prosthetic percept. This biologically grounded model aims to enhance the realism and efficacy of simulated prosthetic vision, facilitating the optimization of cortical visual prosthetic systems.

Deep learning can enhance these simulators by integrating them into end-to-end optimization pipelines. In such systems, a CNN can be used to process input images or video frames and generate appropriate electrical stimulation parameters. The simulator then creates a visual representation based on these parameters, which another CNN evaluates by attempting to reconstruct the original input image. The entire system is trained through backpropagation, where the error in the reconstructed image is used to update the parameters of the networks, optimizing the stimulation parameters for better visual perception.

This deep learning approach allows for the dynamic optimization of stimulation patterns, potentially improving the quality and functionality of prosthetic vision. It enables the simulator to adapt to complex visual stimuli and optimize the information encoded in the phosphenes, making the simulated vision more useful for real-life applications.

add more information on why simulator and VR instead of implants?

However, the current simulator is limited to static images due to scene simplification and limited textures on object. The simulator also does not account for the temporal dynamics of real-world environments. Furthermore, the resolutions of phosphenes are still limited even under constant light intensity, which is much more varied in real scenario's. To address this issue, new models must be developed that can process video streams and generate appropriate stimulation patterns in real-time. Different models for image pre-processing of different situations should be able to adapt to changes in the visual scene, ensuring that the user receives accurate and up-to-date information about their surroundings.

Research

Objective

This study aims to develop a novel approach to generating phosphene patterns in a way that dynamics environments can be visualized in real-time. These dynamic systems as of yet, do not exist and are crucial for the development of visual aid systems that can adapt to more complex and real-world scenarios. If successful, these improved prosthetic systems hold potential of increasing the blind user's experience dramatically.

Approach

Explain the experiments and why they are important. Concretely explain how they will be performed.

Explain the three phases of the study.

Innovation

Explain how the research is innovative and how it will contribute to the field. Briefly go over the cutting-edge technology involved in the study. Maybe go over the caveats and limitations of previous work and how this study will find solutions.

Future Impact

Explain the main goal of the study and why future research will be beneficial.

Timetable

The Gannt-chart goes here with a brief explanation of the different phases.

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Rebuttal

After the first review of the draft, the proposal was revised to address the reviewers' comments. The main changes will be listed below: