State-of-the-Art in Visual Cortical Prostheses: Technological Advances & AI Integration

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Abstract

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 review systematically explores the current capabilities, limitations, and future prospects of visual cortical prostheses, with a focus on the integration of artificial intelligence (AI) to enhance functionality and effectiveness. Key topics include the optimization of phosphene patterns, real-time image processing, and comparisons with other types of visual prosthetic devices. The goal is to provide a comprehensive overview of the state-of-the-art in visual cortical prostheses and propose future research directions.

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

Introduction

Background

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. The concept of using bioelectrical interfaces dates back to the 18th century, with pioneering experiments by LeRoy in 1755 and Volta in 1800 demonstrating that electrical stimulation of the eye can induce visual sensations.

The field of neuroprosthetics has witnessed remarkable progress, particularly with the advent of visual cortical prostheses. These advanced devices offer hope for restoring vision in individuals with severe visual impairments by interfacing directly with the brain's visual cortex (Figure 1). Visual cortical prostheses work by converting visual information from the external environment into neural signals that the brain can process, effectively bypassing damaged visual pathways. 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 (Merabet et al., 2005).

AI has emerged as a pivotal element in enhanc-

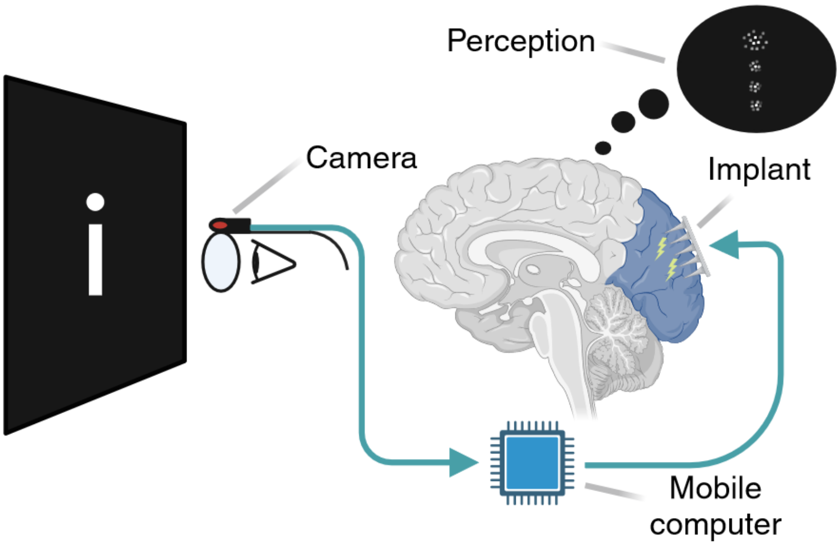

Figure 1 — Functional schematic representation of a visual cortical prosthesis. The visual environment is recorded by a wearable camera and sent to a (wireless) mobile computer. Electrodes within a brain implant are then selectively activated to stimulate neurons in the primary visual cortex (V1). By leveraging the retinotopic organization of V1, a precise pattern of phosphenes is created, forming a coherent representation of the visual scene (Chen et al., 2020). (Image: BioRender, https://app.biorender.com/, accessed on 27 May 2024).

ing these prosthetic systems. By leveraging sophisticated algorithms, AI can optimize stimulation patterns to create more naturalistic visual experiences for users (Kriegeskorte, 2015). AI's role extends to real-time image processing, allowing the prosthesis to adapt to varying visual environments and tasks (Marblestone et al., 2016). This capability is crucial for developing prosthetic systems that closely mimic natural vision, providing users with more effective and adaptable solutions. The integration of AI not only improves the functionality of these devices but also opens new avenues for innovation in how visual information is processed and perceived (Galletti et al., 2001).

This review aims to provide a comprehensive analysis of visual cortical prostheses, focusing on the role of AI in advancing these prosthetics. It investigates current technological advancements, particularly in electrode design, signal processing, and integration. Furthermore, it explores the optimization of phosphene patterns and real-time image processing facilitated by AI, comparing visual cortical prostheses with other types of prosthetic devices, and examining the functional differences between AI-enhanced prosthetic vision and natural visual processing within the human brain. By examining current capabilities, identifying limitations, and proposing future research directions, this work seeks to contribute to the ongoing development of more effective and user-friendly visual prosthetic systems. Combining technological innovation with neuroscientific insights has the profound potential to enhance the quality of life for individuals with visual impairments.

Key Articles

To ground this review, several key articles have been selected that highlight the current state and advancements in visual cortical prostheses:

- Van der Grinten et al. (2024) discuss the simulation of phosphene patterns for optimizing visual experiences (van der Grinten et al., 2024).
- Farnum & Pelled (2020) review the advancements in microelectronic devices and the integration of AI for enhanced visual prostheses (Farnum & Pelled, 2020).
- Grani et al. (2022) explore closed-loop stimulation strategies for real-time adjustments in visual prostheses (Grani et al., 2022).

Technological Advances

Recent years have seen significant progress in the development of visual cortical prostheses, driven by advancements in both hardware and software systems. These innovations are pivotal in enhancing the functionality, efficiency, and user experience of these devices. For an overview of the advances see table 2.

Advancements in Biomaterials and Electrode Design

One major area of advancement is in electrode design and fabrication. Traditional electrodes have been limited by issues such as biocompatibility, stability, and the ability to generate precise neural stimulation. Recent studies have introduced novel materials and fabrication techniques that significantly improve these aspects.

Conductive Polymers

The development of flexible and biocompatible electrodes allows for better integration with neural tissue, reducing the risk of damage and increasing the longevity of the implants. These polymers are especially useful for flexible 3D microneedle electrode arrays and are able to support mesh substrate layers that can support the curvature of various brain tissue (Xiang et al., 2016). Conductive polymers have been instrumental in advancing the design and functionality of these electrodes.

One notable conductive polymer is PEDOT:PSS (poly (3,4-ethylenedioxythiophene) polystyrene sulfonate), which has been widely used due to its excellent electrical conductivity, flexibility, and biocompatibility. PEDOT:PSS coatings on electrodes improve signal transduction and reduce impedance, which enhances the quality of neural recordings and stimulation (Rivnay et al., 2015). Additionally, PEDOT exhibits remarkable stability in physiological environments, ensuring long-term functionality of neural interfaces. Its ability to form thin, conformal coatings on complex surfaces allows for seamless integration with neural tissue, minimizing tissue damage and inflammatory responses (W. Zhang et al., 2022).

Another significant advancement is the use of polyaniline (PANI), a conductive polymer known for its tunable conductivity. PANI can be chemically modified to optimize its electrical properties, making it suitable for long-term neural interfacing applications. Its use in electrode design has shown promising results in maintaining stable performance over extended periods using a silicone matrix (Almufleh et al., 2021). While PANI electrodes are cheaper to fabricate than PEDOT:PSS, their biocompatibility and rigidity while implanted are still areas of investigation. However, this polymer shows promise for future applications using graphene composites (Fang et al., 2024; Y. Liu et al., 2021).

Polypyrrole (PPy) is another conductive polymer that has been extensively studied for neural applications. PPy-based electrodes offer a unique combination of electrical conductivity and mechanical properties that facilitate close contact with neural tissue. Additionally, PPy can be doped with various bioactive molecules, such as neurotrophic factors (NGF/BDNF/GDNF) or Heparin to promote tissue integration and reduce inflammatory responses (E. N. Zare et al., 2021).

Nanotechnology

Advances in microfabrication have enabled the creation of high-density electrode arrays that can stimulate the visual cortex with greater precision, offering the potential for more detailed and coherent visual experiences, whilst minimizing adverse effects such as inflammation which causes glial scarring and encapsulation of electrodes (Ryu et al., 2020).

Nanotechnology has introduced several innovative approaches to enhance the performance and integration of electrodes in visual cortical prostheses. One such approach is the use of carbon nanotubes (CNTs), which possess exceptional electrical conductivity and mechanical strength. CNTs can be incorporated into 3D scaffold electrode designs to improve signal transmission and reduce impedance, thereby enhancing the quality of neural stimulation (Alegret et al., 2018). Additionally, these nanotubes can be interfaced with conductive polymers like PPY to create conjugated polymers that combine the benefits of both to reduce gliosis, improve adaptability and increase charge-transfer efficiency (Shar et al., 2023).

Another promising implementation is the use of graphene, a fairly new two-dimensional material known for its outstanding electrical and thermal properties. Graphene-based electrodes, due to their thinness, are incredibly flexible and highly conductive with a huge surface area. These characteristics are crucial for long-term implantation and stable neural interfaces. Furthermore, graphene has proven biocompatibility in multiple biological scaffolding applications (Li et al., 2013; Sahni et al., 2013). Thus, graphene could be a unique material that bridges modern requirements of electronics, biology and optics (Lu et al., 2018).

Lastly, gold nanostructures have been utilized to enhance electrode performance. Gold nanostructures refer to nanoscale particles or architectures made of gold, typically with dimensions ranging from 1 to 100 nanometers. These structures can take various forms, such as spheres, rods, shells, cages, wires and stars. Gold nanoparticles and nanowires can be used to modify the surface of electrodes, increasing their surface area and improving their electrical properties. This modification can lead to more efficient charge transfer and lower stimulation thresholds (I. Zare et al., 2022). The ability to control the size, shape and surface chemistry can allow for a variety of different physicochemical properties that are necessary for specific applications. In combination with graphene, gold nanostructures can be utilized to provide biosensor functionality in addition to neural stimulation, allowing for the possibility of also recording neural activity (Rauf et al., 2021).

3D Printing

3D printing technology has allowed for unparalleled precision and customization capabilities, allowing for the creation of complex and highly detailed electrode arrays that can be tailored to the unique anatomical features of individual patients (R. Guo & Liu, 2017).

This technology enables the production of electrodes that conform to the specific geometry of the cortical surface, improving contact and integration with neural tissue, thereby enhancing the accuracy of neural stimulation and minimizing potential damage to surrounding tissues (Y. Liu et al., 2019). Advances in 3D printing materials, including biocompatible and conductive inks, have improved the performance and longevity of printed electrodes, providing the necessary electrical properties while maintaining compatibility with neural tissue.

Additionally, the ability to rapidly prototype and produce electrodes using 3D printing reduces manufacturing time and cost, facilitating quicker iterations and refinements in electrode design, which accelerates the development process (Y. Zhang et al., 2019).

The combination of conductive polymers, nanotechnology, and 3D printing allows for the creation of more densely packed electrode arrays that do not incur as many issues with the surrounding tissue, while also providing a more stable and reliable hardware base for the complex demands of prosthetic vision devices and the software that utilizes them.

Improved Signal Processing and Integration

Advances in signal processing and integration enhance the performance and functionality of software that orchestrate the formation of phosphene patterns in higher resolutions. This is supported by high-resolution imaging techniques and sophisticated signal processing algorithms that have significantly improved the precision and reliability of implants while also evaluating their functionality.

High-Resolution Imaging

High-resolution imaging techniques provide detailed maps of the brain's cortical structures. These techniques allow for more precise placement and targeting of electrodes, which is essential for effective neural stimulation and helps prevent unnecessary damage to surrounding tissue. As the amount of electrodes increases, the need for more precise placement becomes more important to ensure that the electrodes are stimulating the correct regions of the visual cortex.

Functional Magnetic Resonance Imaging (fMRI) is one such high-resolution imaging technique that provides high-resolution images of brain activity by detecting changes associated with blood flow. This imaging technique is valuable for mapping functional areas of the brain, ensuring that electrodes are placed in regions that will yield the most beneficial outcomes for the user (Landelle et al., 2021).

Two-photon microscopy allows for deep imaging of living brain tissue with high spatial resolution. This technique is particularly useful for observing the interactions between electrodes and neural tissue over time, providing insights that can guide the design and optimization of electrode arrays (Yang et al., 2024).

Furthermore, the development of near-infrared light compatible (NIR-II) semiconducting polymers has enhanced in vivo high-resolution imaging capabilities. These polymers offer excellent penetration depth and spatial resolution using near-infrared window imaging, which are critical for accurate diagnostics and possible therapeutic applications in neural prosthetics (Kang et al., 2023; T. Wang et al., 2023).

Deep learning techniques have also been employed to enhance the resolution of confocal fluorescence microscopy. By using generative models, these techniques improve the learning ability of imaging systems in the frequency domain, resulting in significantly higher resolution images that are essential for detailed neural mapping (Huang et al., 2023). Some of the types of deep learning models are elaborated in the next section on how AI is integrated into visual prostheses.

These high-resolution imaging techniques are integral to the development of more precise and effective visual cortical prostheses, facilitating better integration and performance of these devices. In the future these techniques may allow for real-time monitoring of neural activity through the use of fluorescence with significant penetration depth into the brain. Thus, these could allowing more downstream stimulation while tracking the effects of the implant.

Wireless Communication

Additionally, innovations in wireless technology have enabled the development of untethered wearable prostheses. Wireless systems eliminate the need for external wires, which not only improves the comfort and aesthetics of the prostheses but also reduces the risk of infections and mechanical failures (Brunton et al., 2013). Advancements in wireless power transfer and data communication have made it possible to deliver sufficient power and high-fidelity signals to the implants, ensuring reliable and efficient operation.

Modern wireless devices, such as the *Gennaris* array described by Rosenfeld et al. (2020), incorporate all necessary electronics within the implant. This system includes a wireless receiver and an Application Specific Integrated Circuit (ASIC) encased in a ceramic capsule, allowing for independent control and power for multiple arrays implanted into the visual cortex. This design simplifies surgical procedures and reduces trauma to major cortical blood vessels (Polikov et al., 2005).

Recent advancements include the development of biphasic quasistatic brain communication (BP-QBC), a technique that significantly reduces power consumption while maintaining high data transfer rates. This method leverages electro-quasistatic signaling to create a low-power, broadband communication channel between wireless neural implants and external devices, offering a promising solution for energy-efficient and high-speed data transmission in neural prosthetics (Chatterjee et al., 2023).

These advancements in wireless communication technology are crucial in order to provide a more seamless and reliable neural interface.

Software and Algorithmic Enhancements

On the software side, the integration of artificial intelligence (AI) has revolutionized the way visual information is processed and interpreted by prosthetic systems. AI algorithms, particularly those based on deep learning, have been employed to optimize stimulation patterns and enhance image processing capabilities. These algorithms can learn from vast amounts of data to improve the accuracy and efficiency of visual signal conversion, making the visual experiences more naturalistic and adaptable to different environments (Romeni et al., 2021).

Real-Time Data Processing

Real-time data processing is pivotal for the functionality of a complex prosthesis that has to generate accurate representations of an environment, especially while a user is moving. Translation of visual information from the external environment into neural signals has to be seamless so that they can be interpreted by the brain's visual cortex.

A key aspect of real-time data processing involves the integration of high-speed computing systems capable of handling large volumes of visual data with minimal latency (Nurmikko, 2020). The processing pipeline typically includes capturing visual information via cameras, preprocessing the data to reduce noise and enhance relevant features, and converting this data into neural stimulation patterns based on the resolution of the phosphene pattern.

Edge computing plays a crucial role in this pipeline by performing data processing closer to the data source. This reduces latency and enhances the responsiveness of the prosthetic system, which is particularly important for real-time applications such as navigation in dynamic environments (F. Wang et al., 2020). By offloading computational tasks from centralized servers to local devices, edge computing ensures that visual data is processed swiftly, enabling immediate feedback to the user.

Another important component is the use of adaptive algorithms in the form of deep learning models that can dynamically adjust to changes in the visual environment. These algorithms leverage feedback from the user's interactions with the prosthetic system to continuously improve accuracy and effectiveness (Pio-Lopez et al., 2021). For example, real-time adjustments can be made to the stimulation patterns based on environmental factors such as lighting conditions and the presence of moving objects, ensuring that the visual output remains consistent and coherent (Fylstra et al., 2022).

Additionally, advancements in sensor technology have significantly contributed to real-time data processing capabilities. High-resolution cameras and depth sensors provide detailed visual information, which is essential for generating precise and informative neural signals. These sensors can capture a wide range of visual cues, including color, depth, and motion, which are then processed to create a comprehensive visual experience for the user (Rueckauer & Van Gerven, 2022).

Real-time data processing also benefits from the constantly improving development of specialized hardware accelerators, such as Graphics Processing Units (GPUs) and Field Programmable Gate Arrays (FPGAs) (Feng et al., 2020; Springer et al., 2021). These devices are optimized for parallel processing tasks and can handle the intensive computational demands of real-time visual data processing. By utilizing these hardware accelerators, visual cortical prostheses can achieve the necessary processing speeds to provide immediate and accurate visual feedback.

In summary, real-time data processing in visual cortical prostheses involves a combination of high-speed computing, edge computing, adaptive algorithms, advanced sensors, and specialized hardware accelerators. These systems work together to ensure that visual information is processed and transmitted to the brain without noticeable delays, creating a natural and effective visual experience for users. This seamless integration of hardware and software components is crucial for the ongoing development and enhancement of visual prosthetic systems.

Other Functional Improvements

Closed-Loop Feedback Systems

Another significant advancement is the implementation of closed-loop systems in visual cortical prostheses. These systems continuously monitor neural feedback to adjust stimulation parameters in real-time, thereby enhancing the precision and effectiveness of visual restoration. Closed-loop systems mimic the natural feedback mechanisms of the human visual system, providing a more responsive and user-friendly experience. Recent research has demonstrated the efficacy of these systems in improving the visual outcomes for users, as they can dynamically adapt to changes in the environment and the user's neural responses (Levi et al., 2018).

Multi-Modal Sensory Integration

The integration of multi-modal sensory input is another promising development in this field. By incorporating inputs from other senses, such as auditory or tactile feedback, visual cortical prostheses can provide a more holistic sensory experience. This multi-modal approach leverages the brain's ability to integrate information from different sensory modalities, potentially enhancing the overall perceptual experience and aiding in the interpretation of visual scenes (Wan et al., 2020).

Technological Advances in Visual Cortical Prostheses

- **Advancements in Biomaterials and Electrode Design**
  - **Conductive Polymers:** PEDOT:PSS, Polyaniline (PANI), Polypyrrole (PPy)
  - **Nanotechnology:** Carbon Nanotubes (CNTs), Graphene, Gold Nanostructures
  - **3D Printing:** Customizable and high-precision electrode arrays
- **Improved Signal Processing and Integration**
  - **High-Resolution Imaging:** Functional Magnetic Resonance Imaging (fMRI), Two-photon microscopy, NIR-II semiconducting polymers
  - **Wireless Communication:** Biphasic Quasistatic Brain Communication (BP-QBC)
- **Software and Algorithmic Enhancements**
  - **Real-Time Data Processing:** Edge computing, adaptive algorithms, advanced sensors, hardware accelerators (GPUs and FPGAs)
- **Other Functional Improvements**
  - **Closed-Loop Feedback Systems:** Dynamic adjustment of stimulation parameters
  - **Multi-Modal Sensory Integration:** Incorporation of auditory and tactile feedback

Figure 2 — Summary of key technological advancements in the development of visual cortical prostheses, highlighting improvements in biomaterials, signal processing, software, and functional integration.

AI Integration

The integration of AI in visual prosthesis systems is focused on how deep learning algorithms enhance visual data processing, optimize phosphene patterns, and emulate normal brain processing. Figure 3 provides an overview of a Visual Prosthesis Simulation Framework based on the work by de Ruyter van Steveninck, Güçlü, et al. (2022). This framework employs AI to simulate and predict how users perceive visual information through a prosthetic device. By integrating deep learning algorithms, the system can accurately replicate and enhance visual experiences.

The functional process of a visual cortical prosthesis in this framework is an end-to-end process that includes three main components: an encoder, a phosphene simulator, and a decoder. The encoder processes the input image to generate a stimulation protocol, which determines the intensity of stimulation for each electrode. The phosphene simulator translates this protocol into a simulated phosphene vision (SPV) representation, incorporating factors like distortions in phosphene positions and brightness variations. Finally, the decoder reconstructs the input image from the SPV representation, ensuring accurate interpretation of the encoded information.

Optimization is a critical aspect, involving automated and tailored adjustments to achieve the best visual reconstruction. Task-specific optimization is implemented by using different loss functions, guiding the network to preserve relevant information. Constraints such as sparsity can be incorporated to minimize adverse effects of electrical stimulation. The modular design allows the system to adapt to practical, medical, or biophysical limitations. Some designs, such as the one by de Ruyter van Steveninck, Güçlü, et al. (2022), have been made open-source to facilitate collaboration and further development.

Deep Learning Algorithms in Prosthetic Vision

An innovative approach is the use of feed-forward neural networks to improve the control of brain-machine interfaces. This simpler neural network architecture enhances the speed and accuracy of prosthetic control by more closely mimicking the natural communication pathways between the brain and the body. Such improves the functionality of prosthetic devices and enhance their usability for individuals with paralysis or limb loss (Willsey et al., 2022). However, these “sim-

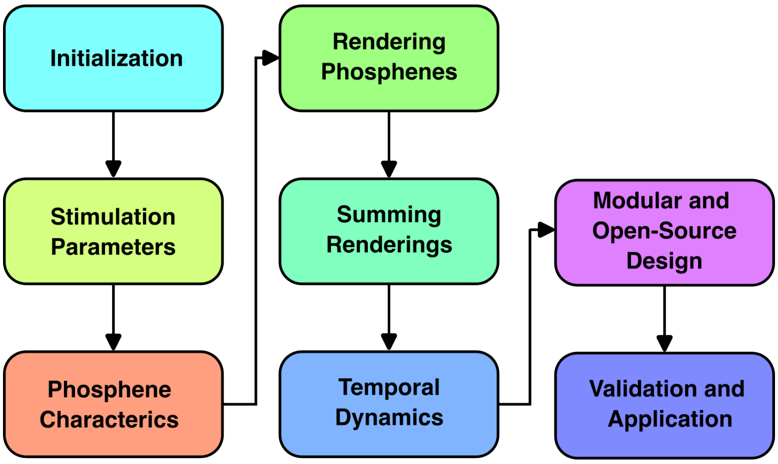

Figure 3 — Overview of a Visual Prosthesis Simulation Framework. The simulator is initialized with electrode locations on a visuotopic map of the visual cortex (V1), representing the spatial organization of the visual field. For each frame, it processes stimulation parameters such as amplitude, pulse width, and frequency for each electrode. Using these parameters and electrode locations, it estimates phosphene characteristics, which are rendered on a visual field map considering cortical magnification and activation thresholds. Individual phosphene renderings are summed to produce the simulated prosthetic percept. Temporal dynamics, including delayed onset and offset of perception, are modeled using a leaky integrator. The simulator's modular and open-source design, implemented in Python with PyTorch for example, allows for fast GPU computations and easy integration with external software (de Ruyter van Steveninck, Güçlü, et al., 2022). It is validated through computational and behavioral experiments, incorporating neurophysiological and clinical findings to ensure biological plausibility.

pler" networks are not suitable for more complex image generation tasks and require on-the-fly learning capability. This is where more sophisticated so called deep learning models come into play, a model that learns to perform classification or regression tasks directly from (image) data.

So why are AI algorithms essential for the development of prosthetic vision? These algorithmic models are in principle, designed as solutions to low sampling resolution. The optimization of phosphene patterns are an area that benefits significantly from preprocessing optimizations of image quality. An example of a spiking neural network is the NeoCube architecture for obstacle-avoidance by F. Guo et al. (2018). This architecture is a prime example of how an AI system can enhance the user experience by adding increased stability and accuracy to the prosthetic system, without the addition of additional hardware.

Deep learning models are different kinds of neural networks that are used to predict and interpret visual inputs without providing environmental context. This is known as saliency mapping, which is an important technique used in deep learning to identify and visualize the regions of an input that most significantly influence the model's predictions. Within the deep learning domain there are however several types of neural networks that are used to enhance the capabilities of models in different ways.

Various types of neural networks exist, including Convolutional Neural Networks (CNNs) for image recognition, Recurrent Neural Networks (RNNs) for temporal data processing, Generative Adversarial Networks (GANs) for generating realistic visual patterns, and Graph Neural Networks (GNNs) for understanding complex spatial relationships, that collectively enhance capabilities in image translation, object recognition, and scene interpretation. These key deep learning algorithms are crucial in predictive modeling, with each contributing uniquely to improving the functionality and performance of visual cortical prostheses. A comparison of these algorithms in prosthetic vision systems is provided in Table 1.

Predictive Modeling

Predictive modeling plays a crucial role in prosthetic vision by leveraging various deep learning algorithms to enhance visual perception for users. These models are designed to predict and interpret visual inputs, creating a seamless and coherent visual experience. By utilizing large datasets and advanced neural network architectures, predictive modeling enables the prosthetic system to anticipate and adapt to dynamic visual environments. Aforementioned key deep learning algorithms are employed in predictive modeling, these include CNNs, RNNs, GANs, and Multidimensional GNNs. While not all of these model types have been explicitly used in visual prosthetics yet, they have significant potential to enhance the capabilities of these systems.

Convolutional Neural Networks (CNNs)

CNNs are employed to process and classify visual inputs, enhancing the ability of the prosthetic system to interpret complex visual scenes and improve object recognition capabilities. CNNs are particularly effective at identifying spatial hierarchies in images through layers of convolutions that capture features like edges, textures, and shapes. By training on large datasets, CNNs learn to recognize a wide range of objects and scenes, enabling the prosthetic system to provide users with detailed and accurate visual information (Petrosyan et al., 2021). This improves the user's ability to navigate and interact with their environment by providing clearer and more recognizable visual cues (Maheswaranathan et al., 2023). An example of such a system was used in one of the key articles by de Ruyter van Steveninck, van Gestel, et al. (2022), where they used SharpNet predictions to create a surface boundary mask. SharpNet is a CNN-based model that allows for estimation of depth and surface normals, which is essential for the formation of meaningful phosphene vision patterns.

Recurrent Neural Networks (RNNs)

RNNs, including LSTM (Long Short-Term Memory) networks, are used to handle sequential data, making it possible to maintain temporal continuity in visual perception and improve the user's ability to track moving objects. Unlike CNNs, which focus on spatial relationships, RNNs excel at processing temporal sequences. They retain information over time, allowing them to predict future frames based on past visual data. This capability is essential for maintaining a continuous and stable visual experience, especially when tracking dynamic scenes or moving objects, thereby enhancing the user's perception of motion and improving their ability to react to changes in their environment (Liao & Poggio, 2016; Nayebi et al., 2022). RRNs in the form of LSTMs have been explored for the use of special conditions such as low-light environments, by enhancing the visual inputs and provide greater image clarity (Ren et al., 2019). In addition, these same specific networks show excellent performance in gesture recognition (Nguyen-Trong et al., 2021), which is an important aspect of human interaction which can be facilitated via a prosthetic.

Generative Adversarial Networks (GANs)

GANs can be utilized to generate realistic phosphene patterns by training on large datasets of visual scenes, improving the fidelity and natural appearance of the visual output. A GAN consists of two neural networks, a generator and a discriminator, which are trained together in a competitive process. The generator creates synthetic images that the discriminator attempts to distinguish from real images (Ledig et al., 2017). Through this adversarial training, GANs learn to produce high-quality, realistic images that can be used to simulate phosphenes—patterns of light perceived by the visual cortex (Elnabawy et al., 2022; Goodfellow et al., 2020). This enhances the naturalness and coherence of the visual scenes presented to the user, making the prosthetic vision more similar to natural sight.

Multidimensional Graph Neural Networks (GNNs)

GNNs are leveraged to model and interpret complex relationships within multidimensional data, enhancing the system's ability to understand and process spatial and relational information. GNNs extend traditional neural networks by operating on graph-structured data, which can represent the spatial relationships between objects in a scene. This allows the prosthetic system to better understand the context and interactions within the visual input. By capturing these intricate relationships, GNNs improve the prosthetic's ability to recognize patterns, structures, and spatial hierarchies, leading to more accurate and

Table 1 — Comparison of Different Deep Learning Algorithms in Prosthetic Vision Systems

Algorithm	Input	Processing	Output	Benefits
Convolutional Neural Networks (CNNs)	Receives raw sensory data from the external world, possibly through a camera or other sensors.	Extracts relevant features (edges, textures, shapes) and identifies objects in the scene.	Generates a pattern of phosphenes that correspond to recognized objects, translating into a simplified image with phosphene "dots" representing different objects or regions of the scene.	Excels at recognizing objects and spatial relationships. Provides basic visual information like identifying objects, their locations, and general scene understanding.
Recurrent Neural Networks (RNNs)	Receives continuous streams of data from the CNN, representing the changing visual scene.	Maintains temporal continuity and tracks moving objects.	Modifies the phosphenes to reflect the movement of objects, allowing the user to perceive dynamic aspects of the world.	Allows for smooth tracking of movement and prediction of future events. Crucial for perceiving the world as a dynamic environment rather than a static snapshot.
Generative Adversarial Networks (GANs)	Trained on large datasets of real-world images.	Learns to generate realistic and diverse phosphenes resembling actual visual patterns.	Produces highly realistic phosphenes for displaying processed visual information.	Enhances perception by creating natural and vivid visual experiences. Generates realistic phosphenes resembling natural light patterns, making prosthetic vision less "artificial".
Multidimensional Graph Neural Networks (GNNs)	Receives spatial information from the CNN, representing relationships between objects in the scene.	Analyzes spatial relationships, understanding context of visual input.	Modifies phosphenes to represent objects and their spatial arrangement and potential interactions.	Enhances spatial awareness and navigation. Understands complex relationships between objects.
How These Algorithms Can Work Together: **CNN:** Acts as the core object recognition system, identifying objects and basic scene features. **RNN:** Adds temporal information, allowing the user to perceive movement and changes in the scene. **GAN:** Ensures that the output phosphenes are realistic and visually appealing. **GNN:** Adds a deeper level of understanding by representing spatial relationships between objects.				

context-aware visual perception. This is particularly useful in complex environments where understanding the spatial arrangement of objects is crucial for navigation and interaction (Subramanian & Khani, 2020; Wu et al., 2021).

Moreover, multidimensional GNNs have been employed to optimize wireless communication policies in neural prosthetics. These networks use graph-based representations to manage complex data transmission scenarios, improving the efficiency and reliability of wireless communication between implants and external devices (S. Liu et al., 2024).

In the future, these algorithms will have to be combined to create a comprehensive AI system that can process and interpret all the varied visual stimuli that a user may encounter and adapt their relative parameters in real time to recreate a faithful representation of the environment.

Comparison with Other Visual Prosthetic Systems

Cortical prosthetics present a distinct and innovative method for restoring vision, setting them apart from earlier retinal and optic nerve implants. Devices such as the PRIMA and IRIS systems by Pixium-Vision, as well as the FDA-approved Orion and ARGUS II by Second Sight Medical Products Inc, have demonstrated their effectiveness. The PRIMA and IRIS systems focus on subretinal and epiretinal placements, respectively, to stimulate remaining retinal cells, making them suitable for specific retinal degenerative conditions (Ho et al., 2015; Muqit et al., 2023).

In contrast, the Intracortical Visual Prosthesis (ICVP) and the Utah Electrode Array exemplify advancements in cortical prostheses. The ICVP uses microelectrode arrays implanted in the visual cortex to provide visual information to blind individuals, offering fine-grained control over neural activation (Troyk et al., 2005). The Utah Electrode Array employs high-density microelectrodes to evoke visual perceptions by stimulating the visual cortex directly, allowing for the creation of more complex visual patterns (Normann & Fernandez, 2016).

These cortical prostheses are uniquely advantageous due to their ability to bypass both retinal and optic nerve impairments and stimulate the visual cortex directly. This downstream positioning is particularly beneficial for individuals with severe visual impairment where other prostheses are ineffective. Additionally, cortical implants offer the longest therapeutic intervention window, leveraging compensatory plasticity mechanisms that recruit neurons from other cortical regions. This enables effective stimulation and rehabilitation long after the onset of injury or disease, significantly enhancing their rehabilitative potential (Beyeler et al., 2017; Tzekov, 2020).

Comparison with Retinal Prostheses

Retinal prostheses, such as the Argus II and the Alpha IMS, focus on stimulating the remaining functional cells within the retina to restore vision. These devices provide visual perception to individuals with retinal degenerative diseases, such as retinitis pigmentosa. The Argus II, for example, employs an epiretinal approach, placing electrodes on the surface of the retina to evoke visual sensations. The Alpha IMS, on the other hand, uses a subretinal approach, inserting the implant beneath the retina to directly stimulate photoreceptor cells (Stingl et al., 2013).

While retinal prostheses have demonstrated significant success in patients with some remaining retinal function, their applicability is limited for those with extensive retinal damage or complete retinal degeneration. In contrast, cortical prostheses offer a broader applicability by bypassing the damaged retinal cells and directly stimulating the visual cortex. This capability allows cortical prostheses to be effective even in cases where retinal prostheses are not viable. Furthermore, the position of cortical implants downstream in the visual pathway leverages the brain's plasticity, potentially offering a longer therapeutic window and enabling rehabilitation well beyond the onset of retinal degeneration (Tzekov, 2020).

Comparison with Optic Nerve Prostheses

Optic nerve prostheses, such as the Epi-Ret3 device and other experimental optic nerve stimulation (ONS) systems, aim to stimulate the optic nerve fibers directly. These devices are particularly beneficial for patients with optic nerve damage, allowing for the bypass of retinal issues. However, the technological complexity involved in precisely targeting optic nerve fibers and the invasive nature of the implantation procedure present significant challenges. The Epi-Ret3 device, for example, has shown potential in preliminary studies but requires highly precise stimulation to be effective (Trieu et al., 2009).

In comparison, cortical prostheses, such as the Orion Visual Cortical Prosthesis and the Intracortical Visual Prosthesis (ICVP), offer distinct advantages by bypassing both the retina and optic nerve. This direct stimulation of the visual cortex enables broader applicability for a wide range of visual impairments, including those resulting from severe optic nerve damage. Additionally, cortical implants benefit from the brain's compensatory plasticity mechanisms, allowing for effective stimulation and visual rehabilitation long after the onset of injury or disease. This extended therapeutic window, coupled with the ability to leverage cortical plasticity, underscores the substantial rehabilitative potential of cortical prostheses for individuals who are blind or visually impaired (Beyeler et al., 2017).

Comparison with Natural Vision

The PRIMA system, as demonstrated in the study by Palanker et al. (2022), represents a significant technological advancement in visual prosthetics, providing a means to restore central vision in patients with geographic atrophy due to age-related macular degeneration. Unlike natural vision, which relies on the complex and highly efficient biological processes of the retina and visual cortex, the PRIMA system uses a subretinal implant to convert images projected from video glasses into electrical signals that stimulate the remaining inner retinal neurons. This artificial method of vision restoration, while impressive, results in visual acuity levels that are still substantially lower than

Table 2 — Comparison of Cortical, Retinal, and Optic Nerve Prostheses

Feature	Cortical Prostheses	Retinal Prostheses	Optic Nerve Prostheses
Target Area	Visual cortex	Retina	Optic nerve
Surgical Invasiveness	Highly invasive (brain surgery)	Moderately invasive (eye surgery)	Moderately invasive (requires access to the optic nerve)
Applicability	Suitable for severe visual impairment with retinal or optic nerve damage	Best for retinal degenerative diseases with some functional retinal cells	Suitable for optic nerve damage with functional retinal cells
Mechanism	Direct stimulation of the visual cortex	Stimulation of remaining functional retinal cells	Stimulation of the optic nerve fibers
Therapeutic Window	Longest, can be effective long after onset of blindness	Requires some residual retinal function	Depends on the extent of optic nerve damage
Technological Complexity	High (phosphene organization and neural plasticity)	Moderate (retinal cell stimulation)	High (complexity in targeting optic nerve fibers)
Advantages	Broad applicability, effective for extensive damage, leverages cortical plasticity	Less invasive, established success in specific diseases, direct visual pathway	Can target optic nerve damage directly, bypasses retinal issues
Disadvantages	Highly invasive surgery, complex visual pattern organization	Limited to retinal functionality, less effective with severe damage	Invasive, technical challenges in precise nerve stimulation
Example Devices	Orion (Second Sight), ICVP (Illinois Institute of Technology), Utah Electrode Array	Argus II (Second Sight), Alpha IMS (Retina Implant AG), PRIMA (Pixium-Vision)	Epi-Ret3, Experimental Optic Nerve Stimulation Systems

those achieved through natural vision. For example, the best prosthetic acuity achieved in the study was 20/460, compared to the near-perfect acuity of 20/20 in natural vision.

Natural vision benefits from the intricate network of photoreceptors, bipolar cells, and ganglion cells within the retina, which work in concert to process visual information with high spatial and temporal resolution. The PRIMA system, on the other hand, must rely on the brain's plasticity and the ability to adapt to and interpret the new, less refined visual signals in the form of phosphenes generated by the implant. While the study showed that patients could achieve functional vision with the PRIMA system, including the ability to recognize letters and basic shapes, this prosthetic vision is limited by the current technology's pixel density and the spatial resolution it can provide. Nonetheless, systems like PRIMA offer a crucial alternative for individuals who have lost their natural vision.

Limitations and Challenges

Quality of Prosthetic Vision

Cortical prosthesis systems, while showing great promise for several types of blind individuals (de Ruyter van Steveninck, Güçlü, et al., 2022; de Ruyter van Steveninck, van Gestel, et al., 2022; Küçükoğlu et al., 2022), artificial vision is far from fully functional. The limits of artificial vision are both due to technological and biological constraints.

Field of Vision

For real-world applicable prosthetic, a wide field of view is essential. Otherwise the user will have trouble to map and interact with the environment (Sugawara et al., 2010). Tasks include: influencing the comprehension of layout space, assessment of walking distance, performance in identify-and-reach tasks, spatial cognition, and attention. Numerous studies have emphasized that restoring a large visual field is essential for artificial vision to be beneficial in daily life. (Subhi et al., 2017; Sugawara et al., 2010). Current cortical devices have a limited field of view of around 16 degrees of visual angle (van der Grinten et al., 2024). Whereas the minimum requirement for sufficient visual information has been established to be at least 30–35 degrees (Sommerhalder & Pérez Fornos, 2017). Furthermore, there it might underestimated that user have to go through rigorous perceptual adaptation and behavioral training in order to make use of artificial vision. Realistically, creating a larger field of view for the user is paired with requiring more implant coverage of the visual cortex, which can lead to possible neurophysiological side-effects due to riskier surgical incisions that have not yet been proven to be safe. Additionally, the arrays used have limited space for extra electrodes, which are already incredibly small and densely packed in Utah arrays for instance.

Spatial Resolution

In addition to a limited field of view, the spatial resolution of current devices also needs significant improvement. In practice this means that the number of distinguishable phosphenes needs to increase. While the technology to create more dense electrodes is available, there is no direct correlation that increase electrode density will lead to a higher resolution.

Surgical and Technological Complexities

The implantation of visual prostheses, particularly those involving the visual cortex, requires highly invasive surgical procedures that pose significant risks, including infection, bleeding, and damage to neural tissues. The complexity of these surgeries can limit the widespread adoption of such systems and make them accessible only in specialized medical centers.

Technologically, creating a seamless interface between the prosthesis and the neural tissue is challenging. The variability in individual neural architecture means that prosthetic solutions must often be highly customized, which can increase costs and complicate the development process.

Limitations in Current AI and Processing Technologies

While AI and advanced processing have greatly enhanced the potential of visual prostheses, they are not without limitations. Real-time data processing requires significant computational power, and delays in processing can lead to a disjointed visual experience. Moreover, the algorithms used to optimize phosphene patterns and visual interpretations need continuous improvement to better mimic natural vision and adapt to various visual environments.

Future Perspectives

Provides a comprehensive overview of the current state and future potential of visual cortical prostheses, highlighting technological capabilities, AI integration, and challenges.

Clinical Applications

A caveat is the invasive nature of these cortical devices, which require surgical implantation.

- Broader and more diverse clinical trials to assess long-term efficacy and safety.
- Exploration of personalized prosthetic solutions tailored to individual neural architectures.

Ethical and Societal Implications

- Considerations of the ethical implications of advanced neural interfacing.
- Societal impact and accessibility of such technology for individuals with visual impairments.

Conclusion

In conclusion, the technological advancements in electrode design, microfabrication, artificial intelligence, closed-loop systems, wireless technology, and multi-modal sensory integration are significantly advancing the field of visual cortical prostheses. These innovations are crucial for developing more effective, reliable, and user-friendly devices that can better restore vision for individuals with severe visual impairments. Continued research and development in these areas promise to further enhance the capabilities and accessibility of visual cortical prostheses, paving the way for their widespread clinical application.

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Rebuttal

- Remove key articles that are not central to the discussion.
- Clearly articulate the research question and objectives in the text.
- Use “visual prosthetic devices” instead of “prosthetic devices” for comparison.
- Narrow down the discussion of technological advances to focus specifically on how phosphenes are formed.
- Explain how AI improves phosphene resolution.
- Move content on software and algorithmic enhancements to the AI integration section.

Main Focus

- Identify and describe the technological advances that best contribute to improved AI usage, focusing on those with the most significant impact.
- Discuss the role of AI in conjunction with high-density electrode arrays, emphasizing how increased density leads to more phosphenes.
- Address clinical and ethical considerations of using AI for object recognition, including decisions on what is important and issues of privacy.
- Ensure the structure includes a stronger connection to AI.
- Emphasize and refine the AI-related table.