# **Restoring High-Quality Vision with Brain-Computer Interfaces: Challenges and Opportunities**

In the past few months, we've heard a lot of discussion around Neuralink and its Blindsight project aimed at restoring vision for people affected by blindness using BCIs.

## Amina Kalandarova

## **But what does Neuralink really have to offer?**

Although Neuralink is creating breakthrough interfaces, the quality of the vision it provides is being questioned.

"I'm leery about the fact that they are very superficial in their description of the devices, …There's no clear evaluation or pre-clinical work that has been published, …It's all based on: 'Trust us, we're Neuralink.'"— said Gislin Dagnelie, a vision scientist at Johns Hopkins University who has been involved in multiple clinical trials for vision prosthetics.

Realistically, if you were to get any BCI vision implant right now, you would see phosphenes. To gain a better understanding of what that means, rub your eyes you will see bursts of light, or phosphenes, randomly firing in your visual field.



an interpretation of seeing phosphenes

Evidently, this is not enough for, or nearly comparable to, the vision humans need for everyday life.

Despite advances, current visual BCIs are limited, offering only rudimentary vision. However, ongoing innovations could enhance these systems significantly. While current BCIs cannot yet offer high-resolution, full-color vision, the advancements being made show promise for future breakthroughs that could meaningfully improve life for individuals with vision loss.

**In this article, we will review the gaps in current cortical implants for vision restoration to understand the challenges holding us back from replicating high-resolution vision.**



progression of vision quality

First, let's recall how cortical BCI implants for vision restoration work…



brain activity: signals passing between neurons

When light enters a healthy eye, it is received by photoreceptors on our retina (the back part of the eye) and is converted into electrical signals. These signals travel through the optical nerve to the visual cortex and further parts of our brain. At each visual area the signals travel to, they are mapped out according to our visual field, but with alterations. For example, if we record the activity on our primary visual cortex when it perceives an image, you will see that it represents the same image, but distorted:



**Retinotopic maps** are used to visualize the spatial arrangement in the primary visual cortex where each neuron represents a specific small region of the visual field, forming a spatial map of the opposite half of the field of view.



retinotopic maps

Cortical brain-computer interfaces for vision restoration work by stimulating the visual cortex of our brain— using implanted electrodes. These electrodes generate electrical pulses that mimic the natural signals produced by healthy photoreceptors in response to light entering the eye. The brain interprets these artificial signals as visual information, allowing the user to perceive basic shapes, light, or movement. BCIs essentially 'hack' the visual system by bypassing damaged areas and reintroducing visual signals directly into the brain.



While we have found out how to replicate signals, there are a few significant aspects that we still have to figure out:

1. **Low Resolution and Limited Field of View**: the images generated are highly pixelated, often equivalent to seeing a handful of light points rather than a clear picture.



visual models of [phosphenes](https://www.sciencedirect.com/science/article/pii/S0042698909000467)

**2. Lack of Color Perception:** Current BCIs struggle with color encoding, restricting the visual experience to shades of gray.

**3. Limited Depth Perception and Object Recognition:** Without depth and object recognition, navigating real-world environments can be challenging for users.

**4. High Cognitive Load:** These systems require significant mental effort to interpret the limited visual information, leading to fatigue and potential cognitive strain.

So what are the challenges we face that restrict us from replicating high-quality vision? There are several issues, mostly under two categories: *technical* and *biological*.

# **Technical Challenges**

1. **Electrode Density and Biocompatibility:** Higher electrode density improves image resolution, but more electrodes increase complexity and can cause inflammation, impacting long-term function.



### [Inflammatory](https://pubs.acs.org/doi/10.1021/acschemneuro.7b00403) Tissue Reaction to Brain Implants

2. **Signal Processing and Decoding Algorithms:** Decoding visual data into patterns that can be interpreted by the brain is difficult. Advanced algorithms are needed to process these signals accurately and quickly.

3. **Power Consumption and Wireless Transmission:** Powering BCIs wirelessly without bulky equipment is critical for user mobility but remains technically difficult, especially considering the need for more electrodes and computation.



inductive charging

4. **Long-term Stability and Durability:** Implants must withstand the body's natural immune response, which can degrade device effectiveness over time.

## **Biological Challenges**

1. **Understanding Visual Cortex Organization and Plasticity**: Visual areas of our brain are extremely complex and not yet fully understood which makes it hard to replicate our visual system artificially. Furthermore, variability in how visual areas of the brain are organized across individuals makes it challenging to design BCIs that work universally.



human brain connectivity

**2. Interfacing with Different Levels of the Visual System**: Stimulating different levels of the visual pathway requires precise, tailored approaches to avoid sensory mismatches. This also relates to the challenge of reaching the right parts of the brain as the areas of the brain responsible for essential aspects of vision such as depth perception and object recognition are located deeper in the brain and are hard to reach.

● This is *also a technical challenge*, as we have to position electrodes precisely enough to stimulate the particular neurons we need. This poses yet another challenge: making sure the electrodes stay in place, as any movement can cause misplacement of stimulation.



The Visual System

As the biological challenges are more research-intensive and data-oriented, today we are going to focus on technical obstacles. Among them, **improving signal processing and decoding algorithms** stands out most.

## **Improving Processing and Decoding Algorithms**

Developing better algorithms for cortical BCI implants could be considered **the most critical challenge** in visual BCIs because these aspects are responsible for translating raw data from our visual field into a format the brain can interpret as meaningful vision, which is the essence of the application of BCIs as a way of vision restoration.

Vision isn't just a matter of light and dark — it involves layers of detail like **depth, color, motion, and object recognition**. To restore vision that feels natural, BCIs

must process this complex information and break it down into signals that mimic the way a healthy eye would send data to the brain.



Visual [Encodings](https://www.youtube.com/watch?v=14FJU1kP6-M)

Additionally, **our brains don't interpret each pixel individually;** they recognize patterns, faces, and objects almost instantly. Decoding algorithms need to adapt and simplify vast amounts of raw data into patterns that mimic this high-level interpretation.

**Lastly, every individual's brain structure is unique**, which affects how visual information is processed. Algorithms that can learn from and adjust to each user's specific brain responses would make the BCI's output more effective, but this requires *advanced, flexible* decoding approaches.

The multi-layer nature of our vision, its pattern recognition, and variability of brain structure among individuals must be considered when improving processing and decoding algorithms.

## **Decoding Algorithms: Status Quo**

**Traditional Machine Learning:** Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), and Random Forests are often used in many BCIs.

**Deep Learning:** Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are increasingly being applied to BCI decoding tasks.



[Convolutional](https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53) Neural Network

### **Processing and Decoding Algorithms: Future**

What technologies are scientists and engineers working on to improve the algorithms? Here are some technologies that the BCI field seems to be moving towards:

**Hybrid BCIs:** Combining multiple brain signals and modalities for improved performance.

**Personalized Models:** Developing subject-specific decoders to address inter-individual differences[3].

**Unsupervised and Self-Supervised Learning:** Reducing the need for labeled training data[1].

**Integration with Computer Vision:** Leveraging advancements in computer vision to enhance BCI visual decoding capabilities[1].

**Improved Temporal Resolution:** Developing algorithms that can better utilize the high temporal resolution of EEG for real-time applications[4].

Recent innovations in decoding algorithms for visual BCIs show promising advancements that could significantly improve the quality of vision offered by BCI implants. Here are some **key innovations** and their **potential impact:**

## **Adaptive Thinking Mapper (ATM)**

A novel EEG encoder that can be used in a plug-and-play manner to extract representations in real-time for both EEG and MEG data[2]. This innovation has several potential benefits for visual BCIs:

**Improved Signal Processing:** ATM's ability to handle different types of neural signals could lead to more robust and versatile visual decoding.

**Real-time Capabilities:** The real-time processing feature of ATM could enable more responsive and dynamic visual feedback in BCI implants.

**Cross-modal Adaptability:** Its ability to work with both EEG and MEG suggests it might be adaptable to various types of neural interfaces, including invasive BCIs.

**Two-Stage Image Generation**



an application of [Two-Stage](https://www.aimodels.fyi/papers/arxiv/giving-hand-to-diffusion-models-two-stage) Image Generation in art

This approach first transforms EEG features into image priors and then reconstructs visual stimuli using a pre-trained image generator[2][3]. This innovation could improve visual BCIs in several ways:

**Enhanced Visual Reconstruction:** By using a two-stage process, this method could potentially produce more detailed and accurate visual reconstructions.

**Improved Generalization:** The use of pre-trained image generators might allow the system to reconstruct a wider range of visual stimuli, even those not seen during training.

**Faster Processing:** Separating the process into two stages might allow for more efficient computation, potentially leading to faster visual feedback.

## **Contrastive Learning**



#### CLIP: Contrastive [Language-Image](https://medium.com/@abdullahsamilguser/clip-contrastive-language-image-pretraining-83b8913cb7eb) Pretraining

Adapting techniques like CLIP (Contrastive Language-Image Pre-training) for BCI applications could improve image embedding and alignment with neural signals[1][2]. This could benefit visual BCIs through:

**Better Feature Extraction:** Improved alignment between neural signals and visual features could lead to more accurate decoding of visual information.

**Reduced Training Requirements:** Contrastive learning techniques might reduce the amount of subject-specific training data needed, making BCIs more practical for widespread use.

**Improved Generalization:** These techniques could help BCIs better interpret novel visual stimuli, expanding the range of visual experiences they can provide.

# **Transfer Learning and Personalized Models**



### Transfer [Learning](https://encord.com/blog/transfer-learning/)

This technique is being explored to reduce the amount of training data needed and to address inter-subject variability. The exploration of transfer learning techniques and the development of subject-specific models[1] could significantly enhance visual BCIs by:

**Reduced Calibration Time:** Transfer learning could shorten the initial setup time for individual users, making BCIs more practical for daily use.

**Improved Accuracy:** Personalized models could better account for individual differences in brain structure and function, leading to more accurate visual decoding.

**Adaptive Performance:** These techniques could allow BCIs to continuously improve their performance for individual users over time.

# **Predictive Decoding Algorithms Using Generative AI**



Keith Haring, Unfinished Painting, 1989. Private collection

Al Generated Attempt to Finish 'Unfinished Painting".

Another AI-heavy idea is to apply **generative AI** models like the ones used in image generation to predict and "fill in" missing visual details based on limited inputs. Generative AI could be used to reconstruct high-quality images from partial or low-resolution data, using predictive algorithms to provide enhanced detail. For example, if only basic shape information is available, the AI could "imagine" a likely detailed scene based on patterns in similar situations. This technique could deliver more detailed and contextually accurate visual experiences, significantly improving the quality of artificial sight even when the input data is sparse.

These innovations collectively have the potential to significantly enhance the quality of vision offered by BCI implants. They could lead to higher resolution visual reconstructions, more accurate interpretation of complex visual scenes, faster processing times, and more personalized experiences.

…so what's the plan?

### **Next Steps for Developing Decoding Algorithms and Signal Processing for High-Quality Vision**

### Step 1 **Expand Neuroscientific Understanding of Visual Processing**

To map how the brain processes different aspects of vision (color, depth, motion, etc.), we need to conduct detailed studies using advanced imaging techniques (e.g., fMRI, electrophysiology) to understand neural responses to visual stimuli. This foundational knowledge will guide how we design algorithms to replicate natural visual processing.

### Step 2 **Create Large Datasets of Visual-Neural Response Data**

To build comprehensive datasets capturing how neural circuits respond to visual inputs, we can use both human and animal models to collect visual stimulus data alongside corresponding brain responses. These datasets will provide the training material needed for machine learning algorithms to "learn" how to translate visual information into neural signals effectively.

### Step 3 **Develop and Train Machine Learning Models on Visual-Neural Data**

Next, we would need to use **AI** and **deep learning** to recognize patterns and structures in visual data that correspond to brain responses. For that, we have to train models on large datasets to decode complex visual information, such as faces, objects, and movement, into neural patterns. We can do that by utilizing techniques like **supervised learning** to associate visual stimuli with specific neural activation patterns. These trained models will enable more sophisticated decoding, moving from basic light patterns to meaningful visual experiences.

### Step 4 **Implement Real-Time, Adaptive Algorithms**

This step involves making decoding algorithms adaptable and responsive to individual brain differences. It requires developing algorithms that adjust in real time based on each user's unique neural responses. Utilizing **reinforcement learning** will allow algorithms to improve with continued user feedback. This personalization will make BCIs more intuitive and reduce the cognitive load, allowing users to interpret visual information more naturally.

Step 5 **Enhance Hardware to Support Faster Processing and Higher Resolution** Then, we'll need to integrate more efficient and powerful processing units within the BCI system to handle high data loads. This will involve designing low-latency processing chips optimized for neural signal decoding and implementing parallel processing architectures to handle complex visual information in real-time. Improved hardware will reduce lag and support more detailed image transmission, allowing for a clearer, more stable visual experience.

These are the steps that the industry is predicted to take to move Brain-Computer Interfaces towards higher-quality vision restoration, making artificial sight more effective and practical for daily life.

The plan above did not go too far from what companies like Neuralink are implementing right now. Here are some **cutting-edge, innovative ideas** that go far beyond current approaches:



#### **Closed-Loop, Multisensory BCIs with AI-Driven Contextual Awareness**

[Closed-loop](https://www.frontiersin.org/journals/human-neuroscience/articles/10.3389/fnhum.2023.1085173/full) brain stimulation systems for improving the quality of life

This implies integrating a closed-loop system where visual BCI algorithms are combined with inputs from other senses, such as *auditory, haptic, and spatial data*, to provide context and improve interpretation. The BCI would not only process visual data but also predict what the user *should* be seeing based on other sensory information and the immediate environment, using **context-aware AI**. For instance, if a user hears footsteps, the system can anticipate and highlight the visual of a moving person. By combining sensory inputs with AI-based context prediction, BCIs could provide a richer, more immersive experience that helps the brain "fill in the gaps" for a fuller visual interpretation.

## **On-Chip AI Processing for Real-Time Image Reconstruction**



#### AI [Chips](https://builtin.com/articles/ai-chip)

Another thing we could do is implement **on-chip AI processing** right at the implant site for **near-instantaneous image reconstruction**. Instead of sending raw data to an external processor, the implant would perform real-time, high-level decoding and reconstruction of visual scenes directly on the chip. This would allow more complex computations (like high-resolution image decoding) to happen right at the source, reducing latency and power demands. This approach could allow for detailed, real-time images that feel more like natural vision, significantly enhancing the quality of artificial sight for users.



# **Neural Networks That Mimic Brain's Visual Hierarchy**

Deep [Convolutional](https://gracewlindsay.com/2018/05/17/deep-convolutional-neural-networks-as-models-of-the-visual-system-qa/) Neural Networks as Models of the Visual System

A more advanced idea would be to create a **neural network architecture** that mirrors the hierarchical processing seen in the brain's visual cortex, from basic edge detection to high-level object recognition. By modeling neural networks to follow the brain's visual hierarchy, BCIs can decode visual information in a way that feels more natural to the user, processing simple elements first and then building up to complex scenes. This hierarchy could lead to a smoother, more naturalistic vision, where users experience refined details and object recognition without cognitive strain.

However, this idea requires loads of research on the organization and functioning of our brain as well as structuring this data and retrieving actionable information, which makes it a particularly challenging idea to undertake.

### **Optogenetic Stimulation for Precise Visual Information**



**[Optogenetics](https://kids.frontiersin.org/articles/10.3389/frym.2017.00051)** 

**Optogenetics** could be used to stimulate individual neurons in the visual cortex with precise patterns of light, allowing for finely tuned visual representation. Optogenetics offer a level of precision that electrode-based systems struggle with. By genetically modifying neurons to respond to light, optogenetics could stimulate specific cells with high precision, potentially allowing for high-definition "pixels" and improved control over color and intensity. This could create much more **detailed and color-sensitive visual representations**, bringing BCIs closer to natural vision.

## **Hybrid BCIs with Brain-to-Brain Interfaces**



This is one of the most *interesting* ideas — combining traditional BCI approaches with **brain-to-brain interface** technology to create a shared, "networked" visual experience. In cases where one user's neural responses to visual stimuli are robust, this data could be transferred to another user in real time. For example, a caregiver or companion with sight could send certain visual information directly to a user's BCI, enriching their experience in specific contexts like navigating a new environment. This innovation would enable a unique type of sensory support, allowing users to share and gain from others' visual perspectives, which could be especially valuable in complex environments.

**High-Bandwidth Wireless Transmission Using Quantum Communication**



quantum [communication](https://www.technologyreview.com/2019/02/14/103409/what-is-quantum-communications/)

As an experiment, we could use **quantum communication** for faster and more secure transmission of visual data from external sensors to implants. Quantum technology, though experimental, could offer much higher data rates and eliminate delays associated with traditional wireless communication. If implemented, this could facilitate rapid and detailed image streaming directly to the BCI. Such a high-speed system would support high-resolution, lag-free vision, making BCIs more effective for navigating dynamic, real-world environments.

## **Direct Cortical Mapping via Electrophysiological "Fingerprints"**

To further personalize the implants, we could develop **individualized cortical maps** that capture each user's unique brain patterns to tailor decoding algorithms specifically to their neural "fingerprint." By mapping each person's cortex in detail, we could create a customized BCI configuration that decodes signals in a way that optimally matches the user's brain patterns, ensuring **maximum compatibility and efficacy**. This tailored approach could greatly

improve the natural feel of artificial vision, making it easier for users to interpret visual data intuitively.



Neuroimaging and Electrophysiology meet Invasive Neurostimulation for causal interrogations and modulations of brain states

Incorporating these strategies would push beyond current BCI limitations, opening up new dimensions for vision restoration and making artificial sight more natural, reliable, and adaptive for users. By tackling these novel challenges, researchers can create transformative advancements in the BCI landscape.

#### **…so what's next?**

While significant progress has been made in processing and decoding algorithms for visual BCIs, there is still a considerable gap between current capabilities and the goal of high-quality visual reconstruction.



We have yet to find out the real impact these technologies can make on visual BCIs. Of course, high-quality vision will require more than changing algorithms, but improving this aspect will be a huge step towards offering a vision quality that is enough for everyday life and improving the lives of millions. All we have to do now is to continue building and coming up with novel solutions to complex challenges posed by visual BCIs.

If you want to stay updated about the latest developments in neurotech, follow me here and on LinkedIn. See you there!



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