Retinal Prosthesis as an Experimental Pathway to the Spike-Based Neural Code

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Abstract

Recent progress in artificial intelligence (AI) has primarily come from scaling compute and data, yet it faces architectural limits, and moving toward artificial general intelligence (AGI) requires engagement with the brain's native spike-based neural code. An experimentally testable, code-level *in vivo* testbed for the neural code is lacking, and the retinal ganglion cell (RGC) layer is among the most durable and biologically viable interfaces within the eye. We reframe the retinal prosthesis as a spike-level experimental interface, generate artificial spike sequences that conform to the RGC neural code without relying on cortical plasticity or *code-agnostic machine-learning* (CA-ML) approaches that do not resolve the underlying neural code, and use these sequences to study rules of the neural code. The objective is neural code fidelity between artificial and biological retinas: for matched visual input, emitted spike sequences should be interpretable by downstream circuits and reproduce the temporal structure of RGC activity above the *noise floor*. We propose possible implementations of the artificial retina and bioelectronic interface, and outline potential approaches for data and biological validation. This work sets out an experimental pathway for probing the neural code and establishes a research trajectory for studies on AGI and the brain's mechanisms of expression.

1 Introduction

Over the past decade, advances in AI have rapidly expanded the range and complexity of tasks accessible to computational methods [1–6]. While architectural innovations have played an important role, much of this recent progress has been enabled by advances in computational power and driven by scaling laws [7, 8], which predict systematic performance gains from increasing model size, training data, and compute. This empirical regularity has prompted speculation that scaling alone might ultimately suffice for AGI, in both academic work [9, 10] and public statements from industry leaders [11–13].

However, sustaining this trajectory faces fundamental architectural constraints, which can be broadly grouped into 4 categories: (i) The *power wall* [14] and *memory wall* [15, 16], where in von Neumann architectures limited memory bandwidth becomes the bottleneck [17], and in state-of-the-art AI systems a substantial fraction of runtime [18] and chip power budget [19, 20] is wasted on data movement rather than computation. (ii) *Architectural capability limits*, as gradient-based ANNs under empirical risk minimization suffer from underspecification [21], shortcut learning [22], and lack of causal representations [23], leaving them below human-level cognitive abilities in compositionality [24] and memory [25] as evidenced by failures in planning [26], autonomous driving [27], and scientific and artistic creativity [28, 29]. (iii) *Explainability*, as modern AI models often function as

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opaque black boxes [30]. Recent methods such as chain- [31], tree- [32], and graph-of-thought [33] or retrieval-augmented generation [34] provide source-grounded steps but remain limited for high-stakes reasoning [30]. (iv) *Data and energy constraints*, since high-quality human text is inherently limited [35] and large-scale AI training faces growing limits in electrical power supply [36, 37].

Neuromorphic computing adopts spikes as a biologically plausible model [38–40], but remains confined to classic benchmarks and has not yielded scalable systems [41, 42], indicating that it has yet to capture the underlying algorithmic principles of the brain. In contrast, reframing retinal prostheses as experimental probes provides a direct testbed, allowing artificial spike trains to be evaluated for code-level fidelity rather than treated only as aids for functional restoration. This perspective motivates our framework, in which we formalize the artificial retina, define equivalence criteria for artificial–biological spike-based neural codes, and outline validation procedures to test their interpretability by downstream circuits. By treating prostheses in this way, we aim to render the neural code of the optic nerve experimentally testable, establishing a tractable entry point for investigating the brain's mechanisms of expression.

2 Related Work

2.1 Consciousness Theories

Integrated information theory (IIT) [43] and the global neuronal workspace theory (GNWT) [44] are the two most influential contemporary theories of consciousness, valued for providing experimentally testable predictions and empirical support [45, 46]. Following the standard distinction between neural correlates of consciousness (NCC) and explanatory mechanisms [47], these theories specify *what* neural patterns accompany conscious states but not *why* such patterns constitute consciousness [48]. This gap motivates the search for experimental entry points at the mechanistic level.

2.2 Explorations Addressing AI Constraints

A variety of approaches have been explored to address the structural limitations of contemporary ANNs. Hardware innovations (compute-in-memory [17, 49], integrated photonic accelerators [50, 51], neuromorphic chips) have been proposed to overcome the von Neumann memory wall and improve energy efficiency. Hybrid and structured learning paradigms (neuro-symbolic approaches [52–54], causal representation learning [55, 56]) are being explored to overcome these limitations for reasoning and generalization. Data-centric strategies (self-supervised learning [57], synthetic data generation [58]) have been developed to address data scarcity and training cost. Explainability research (saliency methods [59], mechanistic interpretability [60], structured reasoning frameworks [32]) seeks to make model decisions more transparent.

Among these directions, neuromorphic computing is most directly related to our work. A central line of research in this domain has focused on spiking neural networks (SNNs) [61–64], including models (LIF [65], Izhikevich [66]) and learning rules (STDP [67], surrogate gradients [68]). Because spiking models are sparse and event driven, executing them on conventional CPU and GPU platforms is inefficient due to synchronization and data-movement, which motivates dedicated neuromorphic hardware [38, 69, 70]. Digital platforms (TrueNorth [71], Loihi [72], SpiNNaker [73]) and mixed-signal memristive circuits [74, 75], exploit event-driven parallelism. Event-based vision sensors [76] extend this paradigm to sensing by producing asynchronous spike streams from visual input. Recent studies show that SNNs can reach near-ANN accuracy on benchmarks (MNIST [77], ImageNet [78]), while dedicated neuromorphic hardware reports orders-of-magnitude energy gains [72, 79]. However, these advantages largely remain confined to classic benchmarks and have not translated into scalable practice [41, 42]. Underlying this limitation, the field faces fundamental difficulty in determining which biological details are essential for algorithmic performance and what abstraction level neuromorphic models should adopt [38, 70].

Recent biohybrid studies have shown that spiking neural networks can directly couple with biological circuits, achieving subcircuit replacement [80], real-time communication [81], and bidirectional hybrid platforms [82]. These demonstrations remain limited to *in vitro* settings, motivating our reframing of retinal prostheses as an *in vivo* testbed for code-level validation.

2.3 Retinal Prostheses

Retinal prostheses aim to restore partial vision in end-stage photoreceptor degeneration [83] by delivering patterned electrical stimulation to surviving inner retinal neurons through epiretinal, subretinal, or suprachoroidal arrays [84]. Representative electrode-array systems include Argus II [85], Alpha AMS [86], and suprachoroidal prototypes [87]. Photovoltaic approaches include microfabricated prostheses such as PRIMA [88, 89] and POLYRETINA [90], and nanomaterial phototransducers such as up-conversion nanoparticles [91], semiconducting polymer nanoparticles [92], and tellurium nanowire networks [93]. Yet despite these advances, current prostheses remain constrained by limited electrode counts and current spread, yielding coarse spatial resolution and low effective bandwidth. Long-term performance often relies on cortical plasticity to compensate for the mismatch between artificial and native neural codes [83, 84]. Accordingly, prior work, including code-directed strategies such as Nirenberg and Pandarinath [94], has framed prostheses primarily as tools for functional restoration, whereas our perspective treats them as experimental probes of the neural code itself.

3 Methods

3.1 Motivation

As outlined in Section 1, our long-term aim is to establish a *feasible* entry point for studying AGI and the brain's mechanisms of expression: an approach that must be neither too complex to be experimentally tractable nor too narrowly focused on medical or engineering purposes. Since the brain is the only known natural system instantiating general intelligence, reverse engineering is the natural strategy. Most contemporary neuroscience still concentrates on firing-rate-based and population-coding analyses of neural activity [95], a view mirrored in ANNs where unit outputs are typically interpreted as average firing rates [61, 96]. Yet the limitations of such statistical abstractions are well recognized [97, 98], with accumulating evidence in both experimental data [99] and methodological critiques [100]. Given these limitations, the logical step is to move one level deeper, from statistical summaries to spike sequences. Biophysical models such as Hodgkin-Huxley [101] capture ion-channel dynamics but are not tractable at system scale, as reflected in the consensus use of simplified neuron models in SNN research [65, 68]. Only by first resolving the spike-level code can we determine whether further layers are necessary. Notably, Lazar and Toth [102] formalize a time-encoding protocol, treating spike times as code symbols with invertible decoding. This yields a formal mathematical model of spike-time coding, but its idealized assumptions have not been validated *in vivo*.

At the whole-organism scale, the most prominent simulation efforts build on connectomics, with *C. elegans* providing the only complete animal connectome [103, 104], and subsequent efforts have implemented SNN-based simulations of its nervous system [105, 106]. These simulations evaluate success at the behavioral level [106], which shows that the connectome wiring can roughly drive locomotion [105]. However, because of degeneracy [107, 108], where similar behavior can arise from disparate internal mechanisms, they cannot reveal the operative neural code or algorithm. Moreover, locomotion critically depends on external inputs such as medium viscosity and substrate friction, which cannot be reproduced one-to-one in simulation [109]. Our purpose, therefore, is to target a tractable biological black box, decipher its neural code and communication channels, and validate them through artificial replacement.

Why sensory periphery?   The senses constitute the brain's inputs, providing well-defined inputs and outputs for spike-level investigation. By contrast, higher cortical areas such as the prefrontal cortex (PFC) integrate heterogeneous inputs and are often studied under ill-defined assumptions and reverse inferences, raising systemic concerns about their tractability as entry points [110–112].

Why vision?   It is the most thoroughly studied sensory modality across relevant disciplines. In neuroscience, the visual pathway is the best characterized in terms of circuitry, cell types, and experimental paradigms [113–115]. In machine learning (ML), vision is among the most extensively studied and advanced domains, with large-scale benchmarks such as ImageNet [116] and models like ResNet [117] and Vision Transformers [118]. In optical engineering, decades of advances in cameras, lenses, and solid-state image sensors such as CCD and CMOS [119] have produced highly mature

hardware. Beyond disciplinary maturity, vision is also the dominant channel of information intake in humans, engaging roughly half of the primate cortex [120] and forming the perceptual basis for higher cognition.

Why retina? Morphologically, the optic nerve appears to be the natural interface, serving as the sole output cable of the eye. A complete eyeball replacement would eliminate the ganglion-cell somata and reduce the interface to an optic-nerve stump. Transected axons in such stumps undergo Wallerian degeneration [121, 122], precluding a stable long-term interface. Consequently, the RGC layer constitutes the most durable and tractable entry point within the eye, coinciding with prosthetic approaches but here reframed as a probe of the neural code rather than a tool for functional restoration. Accordingly, although some prostheses place the interface at the optical front end using cameras or lenses, these components only provide the optical image and do not perform neural encoding. The retina itself performs the neural encoding and thus constitutes the black box to be replaced for validation.

Why not CA-ML? By CA-ML we refer to approaches that rely on training to absorb mismatches without resolving the neural code. Plasticity is acceptable only within native variability once the artificial code is aligned, as quantified on the same basis as S_{floor}. Although CA-ML approaches have shown promising gains in specific prosthesis tasks, our aim is a fully interpretable interface, pursuing fidelity at the level of the neural code rather than relying on cortical plasticity.

3.2 Conceptual Architecture

Our architecture is likewise best understood as a prosthetic design, sharing the same input–output specification, but reframed as a black-box replacement for validation rather than restoration.
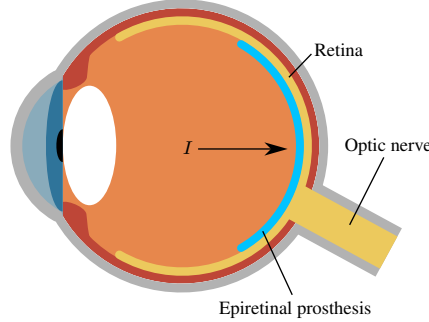

Figure 1: Planar schematic of the visual input–output flow.

In the biological case, light is first shaped by the ocular optics (cornea, pupil, and lens), which are not a bottleneck, before reaching the retina, where it is transformed into spike trains at the RGC layer that propagate through the optic nerve [123]. Formally, let $I(x, y, \lambda, t)$ denote the spatiotemporal optical input after ocular optics. For notational simplicity we denote it simply as I in what follows. The biological retina is modeled as a black-box mapping $\mathcal{B} : I \mapsto \mathbf{s}(\cdot)$, where $\mathbf{s}(t) \in \mathcal{X}^n$ denotes the activity traces of n RGCs over time $t \in \mathbb{R}_{\geq 0}$, with $\mathcal{X}$ denoting the representation space (e.g., spike trains, event sequences, or voltage traces). An artificial counterpart is analogously defined as $\hat{\mathcal{B}} : I \mapsto \hat{\mathbf{s}}(\cdot)$ (Fig. 1). Since the RGC layer lies on the vitreal surface [123], an artificial sheet can be epiretinally placed in direct contact [83], thereby generating $\hat{\mathbf{s}}(t)$ under the same I and comparable output conditions relative to $\mathbf{s}(t)$.

The correspondence between the biological black box $\mathcal{B}$ and its artificial counterpart $\hat{\mathcal{B}}$ is defined at the level of the neural code. The requirement is code-level fidelity rather than exact spike-for-spike identity: $\hat{\mathbf{s}}(t)$ should reproduce the temporal structure of $\mathbf{s}(t)$ such that downstream circuits cannot discriminate them beyond native variability. Formally, S denotes a spike-train similarity function, and we require $S(\hat{\mathbf{s}}, \mathbf{s}) \geq S_{\text{floor}}$. All distance metrics (see Sec. 3.3.3) are monotonically mapped to similarity before thresholding against S_{floor}. Here S_{floor} denotes the *noise floor*, defined as a robust lower bound of biological repeatability (e.g., a pre-registered percentile or confidence bound). This differs from the commonly used *noise ceiling* [124], which is an empirical estimate set by intrinsic

noise rather than a strict constraint, whereas the floor provides the criterion that must be satisfied. This criterion is analogous to a communication protocol: different implementations may generate bitstreams that are not identical at every symbol, yet remain equivalent at the protocol level as long as the receiving system can parse them correctly. Residual deviations are acceptable only when they fall within the intrinsic variability of the native code, quantified on the same basis as S_{floor}.

3.3 Pathways

In implementation, $\hat{\mathcal{B}}$ is composed of a retinal transformation $\mathcal{R}$ of I and a bioelectronic interface $\mathcal{C}$, written as $\hat{\mathcal{B}} = \mathcal{C} \circ \mathcal{R}$.

3.3.1 SNN Implementation

Because the retinal transformation $\mathcal{R}$ must generate biologically structured spike trains, it is natural to instantiate it using an SNN. Unlike generic SNNs that often assume dense connectivity, this instantiation must adopt locally constrained connections, reflecting the network structure of the retina [123, 125, 126]. The connection weights can either be fixed from prior templates, such as receptive-field models [114] or difference-of-Gaussian filters [127], or adapted through biologically inspired learning rules such as Hebbian plasticity [128] or spike-timing dependent plasticity (STDP) [67]. The output spike trains from $\mathcal{R}$ then provide the input to the bioelectronic interface $\mathcal{C}$.

3.3.2 Bioelectronic Interface

The primary engineering bottleneck is channel density, because dozens of distinct RGC types ($\approx$ 30–45 in mouse retina [125, 126]) encode diverse features in parallel, and insufficient independent sites would not only merge signals across types but also collapse spatial information within a type that normally depends on mosaic spacing [129]. Recent photovoltaic prostheses demonstrate the feasibility of scaling channel counts, with POLYRETINA (2215 pixels) [90] and tellurium nanowire implants tested in primates [93]. These advances suggest that device density appears to be approaching ranges that could permit initial exploratory tests of the neural code, indicating that current limitations are primarily practical rather than fundamental.

It remains unclear whether perfect one-to-one correspondence between artificial channels and individual RGCs is necessary. A more tractable starting point is to test whether limited but high-density arrays can already generate decodable neural codes. If hardware density and individualized mapping methods continue to advance, one-to-one correspondence may become attainable, but our framework does not depend on this assumption.

Formally, the bioelectronic interface is defined as $\mathcal{C} : \mathcal{X}^m \to \mathcal{X}^n$, which transduces activity from m stimulation channels into responses of n RGCs. For validation purposes, the details of $\mathcal{C}$ are not considered explicitly. What matters is only the resulting output $\hat{\mathbf{s}}(t)$, which will be directly compared to the biological response $\mathbf{s}(t)$. Achieving code-level fidelity requires both mapping stimulation channels to specific RGC types and mitigating the primary risk of undesired activation of passing axon bundles [130, 131], which must be controlled or explicitly tolerated within defined bounds. Possible strategies include spike waveform clustering [132] in research-grade arrays for type identification, and targeting the axon initial segment [130] to reduce bundle activation, with detailed protocols left for future work.

3.3.3 Validation

At the initial stage, since the neural code is not yet resolved, similarity must be defined operationally rather than by direct reference. We therefore define two levels of validation. At the data level, a noise floor provides the admissible bound for spike-train similarity. At the biological level, acceptance requires that downstream circuits remain within the pre-defined equivalence bound of biological repeatability. Detailed protocols are left for future work.

Validation proceeds in 2 stages: (i) Data validation, which constitutes the theoretical core. (ii) Biological validation, which serves as the strongest proof by demonstrating downstream physiological and behavioral acceptance.

Data validation It involves two elements: obtaining biological spike recordings and defining the metrics for comparison. The approaches discussed here should be regarded as measures for the initial stage, reflecting both the limits of current knowledge and the constraints of available technology. The most advanced tools for the retina are high-density CMOS multielectrode arrays (CMOS-MEAs), which provide near pan-retinal access to large RGC populations and combine large-scale recording with patterned electrical stimulation [133–135]. Although they do not resolve every ganglion cell with single-cell precision, they already permit validation against large recorded populations and can serve as a tractable starting point. For comparison, proxies that can be used include classic spike-train distance measures such as the Victor–Purpura distance [136] and the van Rossum distance [137], time-resolved and parameter-free metrics like the SPIKE-distance [138], recent optimal-transport approaches like SpikeShip [139], and information-theoretic quantities such as mutual information [140, 141]. These proxies allow us to quantify similarity and check admissibility above the noise floor before the neural code itself is fully resolved. Once the neural code is better understood, equivalence can be defined directly in terms of its structure, with classic studies showing that relative spike timing [142], spatio-temporal correlations [143], and higher-order population states [144] are integral components of the retinal code.

Biological validation The same spike-level equivalence criterion applies at downstream levels, with operational proxies used only as interim tools under current experimental limits. This step follows data comparison, providing a proof-of-principle in physiological and behavioral systems. We begin with animals, first testing whether artificial outputs evoke physiological responses in downstream areas such as the lateral geniculate nucleus (LGN) [145, 146] and primary visual cortex (V1) [147, 148]. Next, behavioral assays can test whether animals use artificial signals for perceptual decisions or actions [149]. Finally, these demonstrations should extend to humans, subject to ethical approval and safety validation, aligning with the overarching purpose.

4   Impact

The impact of this work can be considered in 5 aspects: (i) Clinical relevance, by advancing prosthetic strategies for blindness, and theoretical relevance, by providing pathophysiological insight into retinal and ocular diseases. (ii) Cross-sensory extension, as the framework developed for vision can generalize to other modalities such as audition and olfaction. (iii) Philosophical implications, by offering an engineering pathway that turns simulation-theory scenarios [150, 151] into empirically approachable hypotheses, such as whether engineered spike patterns can generate visual percepts indistinguishable from natural vision [152, 153]. At the same time, the framework provides an initial step at the sensory periphery toward the gradual replacement thought experiment [154, 155]. (iv) Meta-philosophical implications, echoing a conceptual lineage from Gödel's incompleteness [156] to the notion of strange loops [157], highlighting whether the brain, as the substrate of cognition, can serve as the instrument with which we attempt to understand it. (v) Transhumanist implications, as code-level prosthetic substitution extends long-standing visions in transhumanist literature, where organ replacement and bodily augmentation have been proposed as routes toward radical life extension and even immortality. [158–160]

5   Future Directions

The immediate focus here is on spike-level code validation, but future progress will require understanding how such dynamics are coordinated across circuits. This broader challenge falls within the domain of complex systems, which offer a natural framework for analyzing such organization. Dynamical-systems formulations provide mathematical tools to capture spike-level dynamics and extend naturally to circuit-scale control [161–163], with their relevance echoed in recent AI architectures such as Mamba [164, 165]. In parallel, emergence [166] highlights how novel properties arise from local interactions that cannot be reduced to single-neuron behavior. In AI literature such effects are often discussed under the label of emergent abilities [167, 168] that appear with scale.

6 Conclusion

We frame retinal prostheses as a starting point for research on AGI and the brain's mechanisms of expression that may ultimately underlie conscious experience. We pursue reverse engineering of the optic nerve's neural code via an RGC interface, synthesizing candidate spike trains for code-level validation. This work should be understood as a proposal at the outset of a research trajectory rather than a definitive solution. A fully restorative prosthesis is not required to be realized, but functions as a tractable entry point through which mechanistic knowledge can be accumulated toward the broader question of consciousness. We hope this work will bring a question once confined to philosophy into empirical inquiry.

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