University of Sussex

# Multi-Sensory Integration via Multi-Ring Architectures in the Insect Central Complex


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# Research Proposal


## Abstract

The insect Central Complex is an evolutionarily ancient neural center essential for flexible navigation and sensorimotor integration. While current computational models of the Drosophila CX successfully replicate heading estimation using a single ring attractor network, recent electron microscopy connectomes reveal a structural redundancy of 46 E-PG cells, sufficient to support three distinct functional rings. This architectural complexity is unaccounted for by current minimal models. This research proposes the Multi-Ring Attractor framework to reconcile this anatomical evidence with circuit function. I hypothesize that this architectural redundancy facilitates parallel processing of disparate sensory streams, specifically allowing for the disentanglement of conflicting visual, mechanosensory (wind), and idiothetic cues before integration. To validate this biological complexity, the study will benchmark the MRA against a standard single-ring attractor, testing the hypothesis that architectural redundancy provides superior context-switching capabilities compared to the collapsed representations of minimal models.

Using the GPU-accelerated PyGeNN platform, I will develop a Spiking Neural Network that instantiates parallel E-PG rings. The project will employ Spike-Timing-Dependent Plasticity to drive emergent specialization of these rings for distinct sensory modalities and investigate conflict resolution mechanisms, such as Winner-Take-All dynamics versus vector averaging. By leveraging the computational expertise available at the University of Sussex, this work aims to provide a mechanistic explanation for multisensory navigation in insects and establish a flexible blueprint for bio-inspired neuromorphic computing.


## 1 Introduction & Motivation

The Central Complex (CX) is a highly recurrent midline neuropil found in all insects, exhibiting a deep evolutionary conservation that spans over 400 million years [15]. Functioning as the interface between higher-order sensory processing and behavioral planning, the CX is the primary substrate for elementary navigational decisions, enabling insects to continuously compare their current heading with a desired trajectory [15]. This region integrates a diverse array of sensory inputs, including celestial compass cues, optic flow, and mechanosensory wind information, to maintain stable orientation and drive complex behaviors such as path integration and migration [37, 15].

Drosophila melanogaster represents a powerful system for dissecting these mechanisms due to the recent publication of the hemibrain connectome [34]. This dense electron microscopy reconstruction provides a complete census of neurons and synapses in the central brain, revealing the precise architecture of the CX [34]. This structural clarity allows us to create biologically constrained spiking networks that reflect the true complexity of the biological substrate.

Research detailing these neural mechanisms has culminated in highly effective computational models [36]. Zhang [44] and Ben-Yishai et al. [2] established the theoretical basis for these continuous attractors, demonstrating how symmetric connections maintain a stable activity packet, or bump, in a marginal phase equilibrium, while asymmetric components drive its shift. Recent work demonstrated that a spiking neural network (SNN) model of the CX, incorporating experimentally derived visual receptive fields, can form a flexible mapping between complex natural scenes and an estimated heading, sustaining this representation even when angular velocity input is absent [36]. This success relies on the principles of the ring attractor architecture, where a single localized bump of activity in the compass neurons (E-PG cells) tracks the fly's head direction relative to its surroundings [36, 43].

Experiments by Sun et al. [38] suggest that single-ring attractor networks are robust, capable of performing optimal Bayesian-like integration and functioning effectively with as few as eight neurons. Despite this computational efficiency, a puzzle persists. The complete electron microscopy-based connectome of the Drosophila CX reveals 46 E-PG cells [34, 16, 36], which is sufficient to form nearly three complete, segregated rings (given that a single functional ring typically requires ∼16 cells to define 8 tiles or 16 wedges) [36].

This structural complexity suggests that the actual biological network may possess redundant capacity [43]. Building on the anatomical evidence proposed by [16, 43], I hypothesize that the observed architectural redundancy in E-PG cell count is functional, facilitating the parallel processing and robust integration of diverse and often conflicting sensory information crucial for navigation and state-dependent action selection. I propose to move beyond single-ring models to construct a Multi-Ring Attractor (MRA) framework. This framework will use parallel E-PG rings within a single integrated SNN to investigate how the CX handles multisensory integration, particularly when faced with contradictory directional cues (e.g., visual landmarks versus wind direction or polarized light orientation). By leveraging the rapid simulation capabilities of the PyGeNN platform [36, 23] developed by Dr Knight and Prof Nowotny, this project is positioned to bridge anatomical discovery with circuit function in one of the most tractable systems for studying recurrent neural dynamics [36, 22].

# 2 The Biological Imperative for Redundancy

The insect CX functions as a highly recurrent central brain region, enabling diverse behaviors such as directed locomotion, memory consolidation, and context-dependent spatial navigation [16]. Stable navigation requires integrating heterogeneous sensory inputs, visual, mechanosensory, and internal state signals, which frequently operate in different reference frames and possess variable reliability [16].

## 2.1 Parallel and Specialized Sensory Pathways

The anatomical blueprint derived from the connectome suggests specialized, parallel input streams converging on the EB. Ring neurons (ER types) serve as the primary conduits for sensory information into the core heading circuit [16, 43]. Distinct ring neuron classes are specialized for unique modalities [16].

**Visual and Polarization Cues:** The anterior visual pathway projects via TuBu neurons through the Bulb (BU) to various ER types [16, 43]. Specific types, such as ER4m, are implicated in processing polarized light e-vector orientations, a reliable celestial cue [16]. Other ER2 and ER4d types process local visual features [36, 43]. The connectome reveals that these inputs often show all-to-all inhibition within and between types, establishing competitive dynamics that prioritize salient visual cues [16, 43].

**Mechanosensory and Wind Cues:** Wind direction cues, essential for flight and navigation, are conveyed to the EB via different ring neurons. Okubo et al. [31] identified R1 and R3a ring neurons as the primary conduits for this information. These neurons effectively compute wind direction by integrating bilateral antennal displacements, transforming peripheral mechanics into a global compass representation. Furthermore, Matheson et al. [26] identified a class of Fan-shaped Body local neurons (hAC) that integrate these wind signals with odor information. This pathway suggests a specialized mechanism for goal-directed navigation where wind and olfactory contexts are disentangled before integration, supporting the hypothesis that the CX maintains segregated sensory streams.

**Internal State and Context:** Other parallel pathways inject internal state signals. ER5 neurons, for instance, track sleep homeostasis [16], while inputs modulated by the Mushroom Body (MB) convey contextual valence signals to the Fan-shaped Body (FB), reinforcing the CX's role in context-dependent action selection [16].

**The Challenge of Dimensional Collapse:** While minimal single-ring models are capable of optimal cue integration via vector averaging [38], this mechanism forces a collapse of dimensionality. In a single ring, conflicting directional inputs (e.g., wind driving a heading estimation eastwards, while polarized light suggests north) must either be fused into a single intermediate bump or resolved immediately via winner-take-all. This prevents the system from maintaining simultaneous, distinct representations of contradictory sensory realities. I hypothesize that the biological redundancy of three rings exists to prevent this premature fusion, allowing the fly to maintain disparate heading hypotheses in parallel and switch contextually, rather than being forced into a single, potentially erroneous mean.

## 2.2 The Multi-Ring Hypothesis

The presence of 46 E-PG cells, enough for three full rings, suggests that this redundancy is the anatomical solution to the challenge of representational collapse [16, 36]. Based on this structural evidence, I propose the following hypotheses.

**Specialized Rings:** I hypothesize that the redundant E-PG rings are specialized to house distinct allocentric heading representations.

> **Ring 1 (Visual/Polarization):** Reflecting the connectivity of ER4m/ER2 types [16], I hypothesize this ring is primarily shaped by segregated visual inputs.
>
> **Ring 2 (Mechanosensory/Wind):** Based on inputs from ER1 types [16], I hypothesize this ring tracks mechanosensory flows.
>
> **Ring 3 (Idiocentric):** Grounded in the findings of Seelig and Jayaraman [35], Turner-Evans et al. [43], I hypothesize this ring acts as a convergence hub or idiothetic (self-motion) anchor, offering capacity for temporary cue storage or unbiased integration.

**Frequency Division Multiplexing:** Building on the concept of specialized rings, I hypothesize that these rings possess distinct resonant frequencies [17]. Ring 1 (Visual) may be tuned to lower frequencies to filter high-frequency jitter in optic flow, while Ring 2 (Wind) may exhibit higher-frequency resonance to capture rapid turbulence. This frequency separation would prevent crosstalk between sensory streams operating at different timescales.

**Conflict Resolution:** I further hypothesize that the ultimate heading signal emerges through continuous arbitration among these parallel representations, rather than sequential selection or hard-coded fusion. This MRA framework moves beyond the traditional view of the single-ring head direction compass [43] towards a dynamically reconfigurable computational module, aligning with the observed complexity of recurrent networks in the brain [16, 43].

Drawing on my research where I developed manifold disentanglement algorithms for robotic state estimation [12] and light-field identification [14], I will approach the MRA as a biological implementation of a filtering process. Just as my robotic algorithms had to weigh noisy sensory streams, the MRA must weigh noisy optic flow against idiothetic cues. I will apply the mathematical principles of uncertainty-weighted fusion used in my robotics work to analyze the conflict resolution dynamics of the parallel rings.

## 3 Physiological Realism and Intrinsic Dynamics

While the Multi-Ring Attractor hypothesis addresses the architectural redundancy of the CX, the dynamical richness of individual insect neurons is often overlooked in standard computational models. Most current models of the Drosophila CX [36, 20] employ Leaky Integrate-and-Fire (LIF) units. While Kakaria and de Bivort [20] demonstrated that ring attractor dynamics can emerge from simple LIF networks given the correct topology, this abstraction discards non-linear intrinsic properties that may be significant for robust multisensory integration in noisy biological environments. To address this, this project will extend the modeling methodology to incorporate three key physiological constraints derived from the attached literature.

### 3.1 Resonance and Frequency Preference

Insect neurons are often resonators rather than simple integrators. Hutcheon and Yarom [17] detail how the interplay between passive membrane properties and voltage-gated currents (such as $I_h$ or $I_{NaP}$) can create specific resonant frequencies, allowing neurons to act as band-pass filters rather than low-pass filters. In the context of the CX, where oscillatory activity is ubiquitous, this intrinsic frequency preference could serve as a mechanism to segregate sensory streams operating at different timescales (e.g., wing-beat synchronous mechanosensation vs. slower visual flow). Standard LIF models fail to capture these subthreshold oscillations.

## 3.2 Electrotonic Structure and Signal Propagation

A physiological feature of Drosophila central neurons is their unipolar morphology, where the soma is separated from the dendritic arbor and spike initiation zone (SIZ) by a thin neurite. Gouwens and Wilson [7] performed patch-clamp recordings on Drosophila projection neurons and revealed that this architecture leads to significant electrotonic isolation. They found that somatic voltage changes attenuate severely before reaching the dendrites or axon, and conversely, unitary synaptic events at the dendrites are heavily filtered before reaching the soma [7]. This implies that the coincidence detection capabilities of these neurons are defined by the specific impedance profiles of their dendritic trees, not just somatic thresholds.

## 3.3 State-Dependent Neuromodulation

The dynamics of insect neurons are state-dependent and not static. Maimon et al. [25] provided direct evidence that active flight profoundly alters the gain of visual processing. They demonstrated that the peak-to-peak response of visual interneurons doubles during active flight compared to quiescence. Suver et al. [39] subsequently identified that octopamine neurons in Drosophila increase their activity during flight, acting as the specific gain control mechanism for this effect. This flight-induced modulation suggests that the integration logic of the CX likely shifts depending on the locomotor state of the animal. A static weight matrix is therefore insufficient. This functional flexibility is further supported by the functional connectome work of Franconville et al. [6], which revealed that the CX connectivity is far sparser than light-level anatomy suggests and relies heavily on bottleneck interneurons like the $\Delta 7$ to organize flow. By constraining the MRA connectivity with the sparse functional maps from Franconville et al. [6] rather than dense anatomical assumptions, the model will rigorously test whether these sparse, modulated, and resonant circuits can support the proposed multi-ring integration.

# 4 Methodology: Developing the Multi-Ring Attractor Model

Realizing the MRA hypothesis requires a simulation environment capable of modeling densely coupled, recurrent SNNs while maintaining biological realism and allowing for extensive parameter exploration. The modeling approach will also control for complexity by implementing a baseline single-ring Touretzky model for direct performance comparison.

### 4.1 Leveraging PyGeNN for Rapid Iteration

This project is anchored by the application of the PyGeNN software ecosystem [36, 23]. While the simulation of $\sim$46 E-PG neurons and their supporting circuitry does not require massive computational resources, PyGeNN offers distinct advantages.

**Efficient Prototyping** PyGeNN (Python wrapper for GeNN) allows for the rapid development and simulation of SNNs [22, 23]. The framework's efficiency reduces the time required for individual simulation runs, which is critical when performing the extensive parameter sweeps needed to tune the interactions between multiple coupled rings and diverse sensory inputs.

**Biological Detail** To capture the subthreshold oscillations and frequency preferences, I will replace the standard LIF units typically used in CX models with the Izhikevich quadratic integrate-and-fire model [19]. I will parameterize the model's four variables $(a, b, c, d)$ to match the impedance profiles of Drosophila neurons, tuning for the resonance and phasic bursting identified by Hutcheon and Yarom [17]. This allows for realistic dynamics without the computational cost of Hodgkin-Huxley simulations.

My background in low-level systems engineering is directly transferable to the optimization of neuromorphic simulations. In architecting a multi-pass quantum compiler [10] and optimizing circuits [9], I solved graph traversal and constraint satisfaction problems to map logical circuits onto restricted hardware architectures. This mirrors the challenge of mapping the dense, hard-wired connectivity of the CX onto the memory hierarchy of a GPU in PyGeNN. I will apply these graph-theoretic optimization strategies to minimize spike-propagation overhead and maximize the simulation speed of the 46-neuron connectivity matrix.

### 4.2 Architecture and Connectivity

The MRA model will instantiate three parallel E-PG rings, each comprising 16 E-PG neurons, 16 P-EN neurons (split into P-EN1 and P-EN2 types for shifting mechanics [43]), and a global $\Delta 7$ inhibitory population shared across the rings [36, 43].

**Core Dynamics:** Each ring will implement the successful ring attractor motifs identified previously: strong local excitatory self-recurrence within E-PGs for persistence [36, 43], angularly shifted excitatory input from P-ENs for angular velocity integration [36, 43], and long-range inhibition via $\Delta 7$ neurons (glutamatergic/inhibitory) to suppress spurious bumps [43, 36].

**Input Layer Structure:** Sensory input layers (simulating different ER types) will be instantiated. These are broadly ER-V simulating visual/polarization-tuned input (e.g., ER4m-like) [16] and ER-M simulating mechanosensory/wind input (e.g., ER1-like) [16].

**Modeling Electrotonic Isolation:** To model the unipolar morphology and electrotonic isolation described by Gouwens and Wilson [7] without full multi-compartmental modeling, I will define a synaptic transfer efficiency parameter. This will be implemented as a filter kernel that applies differential delays and attenuation to inputs based on their distance from the spike initiation zone (distal visual inputs vs. proximal mechanosensory inputs).

Drawing on my industry experience as a research engineer where I led development of a manifold disentanglement algorithm for robotic state estimation improving accuracy by 100x [12], I will similarly investigate if the parallel rings act to disentangle noisy sensory inputs onto distinct low-dimensional attractors before integration.

### 4.3 Emergent Specialization via Plasticity

The specialization of the rings will not be hard-coded initially. Instead, all inputs will project widely, but sparsely, to all three E-PG rings. STDP will be employed to drive the emergent specialization.

**Links to Predictive Coding:** N'dri et al. [29] demonstrates that local inhibitory STDP can implement predictive coding mechanisms by suppressing predictable spiking activity. While there are deep links between STDP and predictive coding in biological networks, I hypothesize that plasticity plays a simpler role in the MRA model.

**Hebbian Dynamics in a Rate-Based Regime:** The MRA model will operate in a rate-based regime where STDP acts largely as a classic Hebbian (or anti-Hebbian) learning mechanism. This allows for the effective tethering of the ring attractor to environmental cues [36]. I will implement the plasticity rules elucidated by Fisher et al. [5] and Kim et al. [21], who showed that visual inputs to the compass are highly plastic. Fisher et al. [5] proposed that this remapping is driven by associative long-term synaptic depression of the inhibitory synapses from R-neurons to E-PG cells. This mechanism ensures that coincident activity weakens the inhibition from specific visual features, disinhibiting the E-PG neurons to carve out the bump location in the compass [5].

**Learning Rule** The model will employ a local anti-Hebbian STDP rule at the sensory-to-E-PG synapses [36, 18].

Given the complex firing patterns introduced by the Izhikevich model [19], standard STDP may be unstable. I will therefore explore trace-based learning rules compatible with burst-dependent plasticity to ensure that rapid bursting events, common in insect resonance, effectively weaken inhibitory synapses ($W_{ij} \to W_{max}$) to carve out the bump location

**Emergence** By differentially stimulating the input layers (ER-V, ER-M) with realistic, modality-specific signals (e.g., high-frequency pulses for wind cues, continuous polarized patterns for ER-V), the Hebbian nature of the STDP rule will cause one ring to become strongly coupled to the most temporally reliable input signals it receives. This allows the rings to partition and specialize their functional roles naturally based on input statistics rather than complex error propagation [8].

This focus on emergent specialization is informed by my work on Adversarial Curriculum Generation [11], where I demonstrated how pressure drives the emergence of complex strategies. I will apply these insights to ensure the plasticity rules implemented in the MRA model are sufficient to drive robust functional differentiation.

### 4.4 Inter-Ring Integration and Conflict Resolution

The test of the MRA hypothesis lies in how the three parallel representations interact and resolve conflict. I propose testing three mechanisms.

**Winner-Take-All (WTA) Arbitration:** Implement strong lateral inhibition between the three E-PG rings (e.g., via a shared inhibitory interneuron or direct inhibitory E-PG $\to$ E-PG connections). This mechanism, observed in other multisensory systems (e.g., between ring neuron types themselves [43, 28]), would enforce that only the representation derived from the currently most reliable or temporally dominant cue persists, suppressing the others [16].

**State-Dependent Arbitration:** To test the hypothesis derived from Suver et al. [39] regarding state-dependent gain control, I will implement a global variable flight state ($G_{flight}$). During quiescence ($G_{flight} \approx 0$), I hypothesize the network will employ vector averaging, fusing cues for stability. During active flight ($G_{flight} > 1$), simulating octopaminergic modulation, I hypothesize the gain of the visual ring will increase, triggering a **Winner-Take-All** dynamic where visual cues suppress conflicting wind inputs to ensure robust trajectory holding.

**Vector Averaging/Fusion:** Implement weak, reciprocal excitatory coupling between the E-PG populations. This soft interaction allows the activity fields to mutually influence each other, potentially resulting in a fused representation (vector summation) if cues are close, or a metastable state if cues conflict, mirroring complex phenomena in biological decision-making [4, 32]. This capability is biologically essential as Behbahani et al. [1] showed that Drosophila can re-zero their path integrator at the center of a food patch and maintain this vector memory even after the cue disappears. I hypothesize that the MRA facilitates this by allowing one ring to maintain the home vector (via re-zeroing) while parallel rings continue to track instantaneous heading, avoiding the catastrophic loss of location memory that would occur in a single-ring system during resetting.

My previous research on Multi-Agent Reinforcement Learning investigated how independent agents establish consensus on a shared world state [13]. I will treat the three parallel E-PG rings as a multi-agent system, where each ring proposes a heading hypothesis based on its specialized sensory modality. I will test the model under conditions where input signals deliver conflicting heading estimates (e.g., high-frequency wind input suggesting a 90° turn, countered by a static visual landmark demanding fixation). This will elucidate which integration topology (WTA or averaging) allows for the most robust and biologically plausible heading estimate [16, 28]. The use of EventProp for training will allow exact gradients to be calculated efficiently for parameter optimization [30].

### 4.5 Comparative Analysis: Single vs. Multi-Ring Dynamics

To validate the Multi-Ring architecture, I will conduct a comparative analysis against a single-ring control model derived from the Touretzky architecture [38]. I aim to determine whether the biological redundancy of E-PG cells offers a functional advantage.

**Benchmarking Dynamics:** In addition to architectural comparisons, I will benchmark the resonant MRA [19] against a standard LIF MRA. I predict the Resonant model will show superior signal-to-noise ratios when tracking high-bandwidth signals (like turbulent wind) due to the intrinsic band-pass filtering properties of the neurons, addressing whether further mimicking the physiology provides computational benefits.

Recent analysis of the classic Touretzky ring attractor suggests that a single ring requires no complex re-weighting mechanism to combine cues according to their certainty. Sun et al. [38] reported that a single ring attractor combines cues via optimal integration for moderate cue conflicts but naturally converges on the most certain cue for larger conflicts. This transition from integration to selection is consistent with ethological observations in animals. Furthermore, this performance was shown to be robust to noise and miniaturization, functioning effectively with as few as 8 directional neurons.

Therefore, I will implement this single-ring integration model in PyGeNN as a baseline. I will subject both the single-ring control and the proposed MRA model to identical conflict scenarios where cues vary in variance and angular disparity. This will determine if the MRA provides superior disentanglement of conflicting modalities compared to the single-ring solution, which may treat all inputs as a single compounded Gaussian distribution. This investigation will clarify if the fly's 46 E-PG cells are serving to create three distinct functional rings as hypothesized to prevent representational collapse, or one highly robust ring capable of MLE-like integration.

## 5 Conclusion

This project requires a unique confluence of domain expertise and specialized computational tools, placing the University of Sussex at the frontier of this research area.

### 5.1 Ideal Environment at the University of Sussex

The University of Sussex hosts Professor Thomas Nowotny and Dr James Knight, developers and maintainers of GeNN and PyGeNN [22, 23]. Iteratively integrating advanced SNN learning rules like EventProp [30] into the novel multi-ring architecture will be most efficient using deep integration with the GeNN framework, an advantage available in this laboratory.

Professor Nowotny's expertise in multi-modal sensing, particularly chemical and olfactory systems [3] can offer guidance in formulating the logic for integrating non-visual modalities (such as wind, which acts as a directional cue for upwind navigation [16, 28]). This combination of software engineering mastery (PyGeNN/EventProp) and deep domain knowledge (Insect Vision/Navigation) establishes the University of Sussex as the most viable location for this project.

### 5.2 Research Impact and Broader Significance

**Biological Insight:** This project directly addresses the structural redundancy found in the fly connectome [16, 36]. Resolving this puzzle advances our mechanistic understanding of how a nervous system, even a small one, organizes complex sensory information streams. The predicted specialization and interaction mechanisms (WTA vs. averaging) provide testable hypotheses for electrophysiological experiments in behaving insects [16].

**Computational Neuroscience and AI:** The MRA model provides a high-impact template for building robust and sparse recurrent SNNs. The results will inform efforts in brain-inspired computational intelligence, particularly concerning how neural activity is routed and processed in complex networks alongside work by MacDowell et al. [24]. The mechanism of parallel, specialized computation resolving into a unified output is reflected in broader theories of perception (e.g., Hybrid Predictive Coding [42, 40]) and the shallow brain hypothesis, where parallel processing paths rapidly converge [41]. Moreover, investigating how the network manages variable reliability through precision-weighted sensory inputs relates closely to advanced Bayesian inference frameworks [27, 3, 33].

**Neuromorphic Engineering:** As neuromorphic hardware matures, there is an urgent need for biologically constrained, highly efficient SNN models that can perform complex, real-time tasks [36]. Simulating multisensory integration in a core navigational module using sparse, spiking activity aligns perfectly with the goals of energy-efficient edge computing [22]. The implementation methodology developed here will serve as a blueprint for implementing functional cognition circuits on platforms like Loihi [36].

**Conclusion:** The proposed research, Multi-Sensory Integration via Multi-Ring Architectures in the Insect Central Complex, represents an evolution from foundational single-ring models to biologically accurate, multi-modal systems. By tackling the challenge of architectural redundancy using the advanced simulation capabilities of PyGeNN, this project promises to yield deep mechanistic insights into biological navigation while delivering a practical, robust blueprint for next-generation neuro-inspired computing. This work is precisely aligned with the cutting-edge research and tool development championed by the computational neuroscience community at the University of Sussex, and I am confident in my ability to deliver results of significant biological and computational impact.

# Personal Statement

## 1 Research Motivation

I am captivated by the open challenges in machine learning that biology evolved to solve. Backpropagation can be inefficient due to global error signals while static architectures seem to lack the plasticity to prevent catastrophic forgetting. This rigidity in vision models appears to cause poor generalizability and vulnerability to adversarial attacks. **I am motivated to research how integrating the principles of computation from biological substrates may reduce these limitations**.

## 2 Selected Research Experiences

My research with Drs. Hanna, Sala, and Berland has resulted in **eight first-author full-length papers: five peer-reviewed publications in NeurIPS** workshops (four in archival proceedings), one in BRAID, and two preprints under review.

**World Models for MARL.** Contributing to my team's **first-place finish at RoboCup**, the international MARL robotics competition, I led a group investigating inter-agent communication. We found that an emergent strategy, inspired by signaling in simple organisms, collapsed despite stabilization. Pivoting to experiment with a **world-model based approach** improved to 96.5% success, revealing the value of an agent internally simulating the environment.

**Active Inference & Structural Plasticity.** Inspired by theories of intelligence like the free energy principle, I addressed the intractability of **active inference** by developing a novel approximation using **principles from RL**. **Dr. Michael Levin invited me to extend this research under his mentorship**. Without a reward, the model maintained 82% success in Cart Pole, forming a step towards computable active inference.

**Visual-Cortex Architecture.** I led a team experimenting with **primate visual cortex architectures** for light field identification. We implemented biological features including **dual-stream processing and predictive coding**. The model achieved 74.4% accuracy, outperforming the next-best by 2.3 percentage points while being 2.5 times smaller, and demonstrated the value of inductive bias through geometric neuroscience.

**Industry Embodied AI.** I **lead state estimation research** at an industry AI R&D lab. State-of-the-art (SOTA) algorithms proved unsuited for our constrained hardware and low-accuracy sensors. I developed an algorithm reducing dimensionality by disentangling data manifolds. The algorithm achieved over 100x improvement in accuracy over SOTA and is now **deployed on all company robots**.

## 3 Research Leadership and Mentoring

**I founded and direct the Wisconsin Neuromorphic Computing and NeuroAI Lab**, securing formal funding, dedicated space, support from Dr. Akhilesh Jaiswal as advisor, and partnership with neuroAI startup FinalSpark. My role involves **mentoring 15 undergraduate researchers**, developing research proposals, organizing biweekly workshops, and lecturing on topics like spike-timing-dependent plasticity drawing audiences of over 100 undergraduates, graduates, and professionals.

## 4 How a PhD Fits My Career Goals

Researching in industry, my development process was one of empirical iteration. I realized a deeper understanding of underlying mathematical theory may yield more efficient solutions.

My long-term objective is conducting **research within a group like DeepMind's neuroscience lab**. Conversations with the current and previous lead, Drs. Kim Stachenfeld and Matthew Botvinick, solidified a PhD as the essential path to gain the theoretical depth and research freedom required. Receiving an **invitation from Dr. Karl Friston** to present my prospective doctoral research at his theoretical neurobiology group reinforced the value of a PhD for engaging with these ideas.

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