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Zhou, B., Sun, P. S. V., Yik, J., Van den Berghe, K., Frenkel, C., Reddi, V. J., & Basu, A. (2025). Grand Challenge on Closed-loop Neural Decoding for Motor Control of non-Human Primates. In M. Nunez (Ed.), *Proceedings of the 2025 IEEE Biomedical Circuits and Systems Conference (BioCAS)* (pp. 324-328). (Proceedings - 21st IEEE Biomedical Circuits and Systems, BioCAS 2025). IEEE. https://doi.org/10.1109/BioCAS67066.2025.00077

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2025 IEEE Biomedical Circuits and Systems Conference (BioCAS) | 979-8-3315-7336-2/25/$31.00 ©2025 IEEE | DOI: 10.1109/BioCAS67066.2025.00077

Grand Challenge on Closed-loop Neural Decoding for Motor Control of non-Human Primates

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***Abstract*—Brain Machine Interfaces (BMI) that record signals from the motor cortex and translates these "thoughts" to action provides hope to paralyzed people. A high-accuracy decoder is needed for a seamless user experience. At the same time, it needs to be compact and low-power to support its integration in an implant to enable the compression required in wireless implantable BMIs. Hence, a model with a good trade-off between accuracy and resource requirement is desirable and was the subject of the 2024 Grand Challenge at BioCAS based on pre-recorded datasets. However, in real-life, the usage of brain-controlled prosthetics, the result of decoding is presented to the user through visual feedback resulting in a closed-loop system. Hence, in the IEEE BioCAS 2025 conference, we organized the first grand challenge on *Closed-Loop Neural Decoding* (http://1.117.17.41/neural-decoding-grand-challenge/). The challenge requires users to move a cursor from a given start position to a target position based on spikes generated from a brain simulator. The evaluations were performed using the recently developed Neurobench software suite for benchmarking neuromorphic systems and the top 3 teams are invited to present their works in the IEEE BioCAS 2025.**

***Index Terms*—Closed-loop, machine learning, implantable BMIs, benchmarking, neuromorphic systems**

I. Organization of the Grand Challenge

A study published in 2013 estimates that approximately 6 million people in the US live with paralysis [1]. This significant prevalence has prompted the development of a variety of assistive technologies designed to restore the capacity for daily living activities. Among these advancements, the intracortical Brain-Machine Interface (iBMI) is regarded as one of the most promising. iBMIs aim to substantially enhance the quality of life for patients impacted by spinal cord injuries or severe neurodegenerative conditions, including tetraplegia and amyotrophic lateral sclerosis etc. These systems employ neural activity as input to control effectors such as computer cursors [2], wheelchairs [3], and prosthetic limbs [4], facilitating communication, mobility, and artificial hand manipulation, respectively. Recently, initiatives have been launched to employ similar technology in addressing speech disorders by transforming imagined speech into a linguistic output [5].

This research was supported by the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. CityU 11200922)

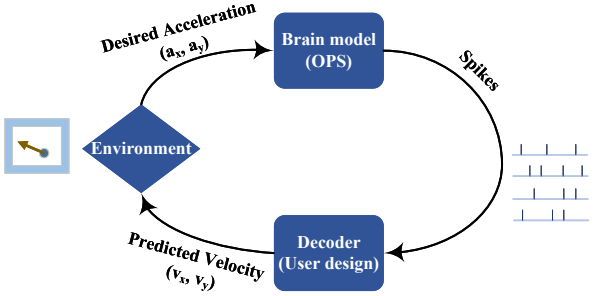


Fig. 1: The test setup for closed-loop system. The challenge provides a brain model that generates spike trains depending on user intent which is based on the desired target location. Users have to design a decoder that predicts intended velocity of cursor movement which results in the environment updating the present cursor location. This completes the feedback loop which results in generation of a new spike train.

Wireless iBMI can address two significant challenges of invasive systems: the risk of infection associated with a skull opening and the limitations on mobility due to wiring connected to a computer. However, this also raises scalability issues, since wireless iBMIs struggle to achieve data rates beyond a few tens of Mbps [6], [7] due to increased bit-error rates, low run-time between battery charges, as well as power dissipation constraints within cortical implants of 80 mW/cm2 [8]. As a result, the number of recording channels is restricted to about 100 (≈150-200 neurons) [9]. Hence, it is essential to investigate methods for compressing neural data to fit within the wireless budget available for implants. Numerous methods such as compressive sensing (CS) [10] or Autoencoder (AE) [11] have been proposed for the compression of neural data. However, only the integration of decoders (Dec) [12]–[14] within the implant presents a scalable solution. This highlights the importance of developing new neural decoders that achieve an optimal balance between accuracy and resource utilization, thereby improving their suitability for implantation.

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The 2024 IEEE BioCAS Grand Challenge [15] was a first step in that direction and pushed the boundary for open-loop neural decoder design using pre-recorded neural data. However, in real-life, usage of brain-controlled prosthetics, the result of decoding is presented to the user through visual feedback resulting in a closed-loop system. The optimal parameters of closed-loop decoding are known to be different from open-loop decoding [16], [17]. Hence, this year, we present the 2025 IEEE BioCAS Grand Challenge on Closed-Loop Neural Decoding. Moreover, the importance of closed-loop benchmarks and their paucity is well accepted in the field of neuromorphic computing [18]. We hope this Grand Challenge serves as a good benchmark for neuromorphic engineers and bridges these two fields of neural and neuromorphic engineering.

II. Simulator

In Figure 1, we illustrate the closed-loop test setup where the Brain-model (also referred to as Online Prosthesis Simulator (OPS) following [16]) is given to the user while the user has to design a decoder. In this challenge, we used a center-out task. The targets (green point) are placed at random locations a fixed distance (8 cm) away from a central starting point (blue point). Participants need to move the virtual cursor from the start point to the target point.

The input to the OPS is the desired acceleration (with a dimension of 2, representing x and y) calculated based on the velocity predicted by a decoder. This is based on the assumption that the participant always attempts to move in the direction of the target. The OPS generates neural activities as potentially recorded on a micro-electrode array (MEA) implanted in the motor cortex. The generated neural signal is sent to the decoder to obtain the predicted velocity, and close the loop. A reach is considered successful when the cursor stays within the circle (light green circle, 2.5 cm) surrounding the target for at least 500 ms, and the total time taken for the successful trial is less than 3.0 s.

The design of OPS in this challenge follows [16]. The input of OPS is the acceleration vector with a dimension of 2, while the output is the neural spike train with a dimension the same as the number of channels in the MEA. The neuron model used in OPS is the cosine tuning model [19]:

$$\lambda_t = (\lambda_{max} - \lambda_{min}) c_k \cdot a_t + \lambda_{min} \tag{1}$$

where c_k, λ_{min} and λ_{max} represent the neuron's preferred direction, minimum firing rates and maximum firing rates respectively. a_t is the desired acceleration vector a at time t. The maximum firing rate is sampled between 40 and 100, while the minimum firing rate is sampled between 0 and 5 spikes per second [20].

III. Grand Challenge

A. Closed-loop Tasks

1) Track 1: Obtaining best time-to-target: The challenge requires participants to move a cursor from a given start position to a target position, utilizing signals produced by the OPS that simulate a 96-channel multi-electrode array. The trial is considered complete if the cursor stays within a specified radius of the target for a specified amount of time.

2) Track 2: Closed-loop with perturbations: Similar to Track 1, but in this case, we induce shifts in the distribution of neural data generated by OPS similar to what happens in real-life implants [20]. The following perturbations were added:

- Loss of neurons (LN): The signal will be set to zero on a random subset of probes mimicking the loss of signal due to increase in impedance in implants over time due to scar tissue formation.
- Electrode Shift (ES): The distribution of signals in a fraction of the probes will be changed mimicking the capture of signals from different neurons due to a shift in the position of the probe.

B. Evaluation Criteria

In this grand challenge, we employed three distinct metrics to evaluate the tradeoff between cost and quality of the models. Average time to target is the first criterion. It is calculated by averaging over 50 trials with various target locations and 3 different instances of the OPS using different random seeds. Participants have to suggest *one* network architecture for all 3 cases, while the parameters or weights can be different for the 3 cases. Memory Footprint is the second criteria. The memory footprint of the model in bytes. The third criterion is Synaptic Operations (Dense/MACs/ACs). The number of synaptic operations of the model. Dense refers to the total number of operations, including operations that involve zeros. MACs refers to the total number of Multiply-Accumulate operations relevant to Artificial Neural Networks (ANNs), while ACs denotes the total number of Accumulate operations specifically utilized for Spiking Neural Networks (SNNs). The metrics can be generated directly from the code harness described below.

C. Code Harness

For this challenge, the closed-loop environment, and evaluation metrics are all encapsulated with the NeuroBench algorithm benchmark, a community-driven project [21]. Each submission used this common framework for loading data and benchmarking algorithms.

For this challenge, the participants were given two classes for their closed-loop simulation, OPS and OPSEnv. In addition, it includes a suite of benchmarks of interest to neuromorphic algorithms, including event camera vision, continual learning, and sequence forecasting. Given a trained model and an evaluation dataset, the harness automatically tests the model on the dataset, and calculates metrics at runtime. The metrics measure not only the correctness of the model, but also its computational costs.

IV. Summary of Participants

A total of 10 teams from around the globe, from 8 universities/organizations/institutions have registered for this competition, which aims to investigate closed-loop neural decoding

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algorithms with energy-efficient strategies. The registration phase commenced on Apr 25 2025 and concluded on May 23 2025, with the deadline for solution submissions set for July 11 2025. The regional distribution of participants is presented in Table I.

To ensure high quality of the accepted papers, we manually reviewed the code submitted alongside the results presented in each paper. The final ranking is based on the output results generated by the code as well as the quality of the papers. Ultimately, the top three teams were invited to present their work at IEEE BioCAS 2025.

TABLE I: Region Distribution of Participants

Region	Number of Teams
America	1
Asia	4
Europe	3
Africa	1
Unknown	1

V. Summary of the Top 3 Winning Teams

Table II reports the statistical results of the top-3 teams for track 2, Fig. 2 and Fig. 3 illustrates the performance comparison between top-3 teams from various perspectives. All results are averaged over 50 trials with 3 different sets of neurons in the OPS. It can be seen from Fig. 2 that the team "Synaptic Circus" achieves much lesser computes than the teams "IRIS Lab" and "SPICE", while taking much less time to target than team "Beach" on Track 1. In Track 2 (Fig. 3) also, the same team achieves better performance under practical ranges of perturbations. Note that the team "Beach" did not participate in Track 2. Therefore, their results are excluded from the tables and figures related to Track 2.

A. Team Synaptic Circus

Thomas Summe et al. [22] from the University of Notre Dame won first place in this contest. Unlike the other teams using deep Spiking Neural Networks (SNNs), they found that only a linear decoder is capable of perfectly addressing the grand challenge of Track 1. Although the linear decoder also performs well in Track 2 till a perturbation ratio of 0.6 (Fig. 3), it does not converge at higher perturbations. Therefore, to achieve optimal performance in track 2, two methodologies were employed for training SNNs: Permutation-Trained and Random-Trained. The Permutation-Trained method utilizes the replacement of predefined neurons, whereas the Random-Trained method employs the replacement of neurons selected randomly. Overall, the simple linear decoder achieves the best trade-off between cost (only hundreds of footprint and ACs) and time-to-target (about 0.8s), providing a new perspective on the design of the energy-efficient decoder for iBMI. The linear model's excellent performance also stems from the fact that the brain-model inherently lacks memory and generates new neural states at every time step based on the input alone. This points to the need for better OPS design in the future.

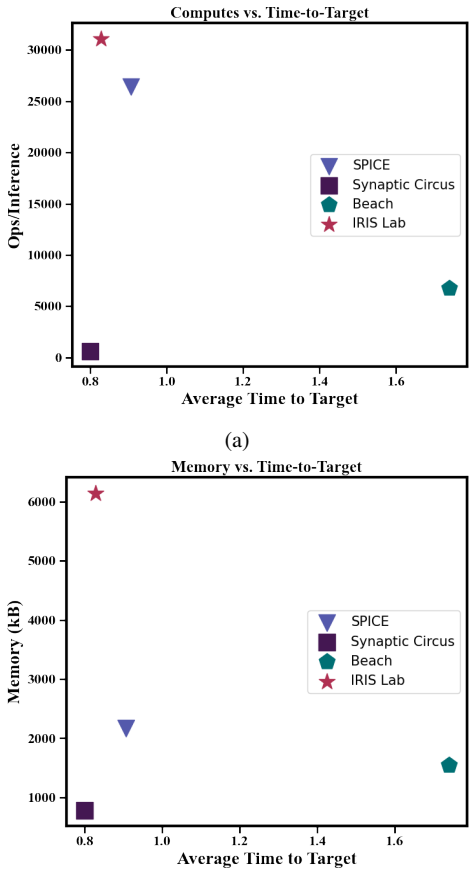
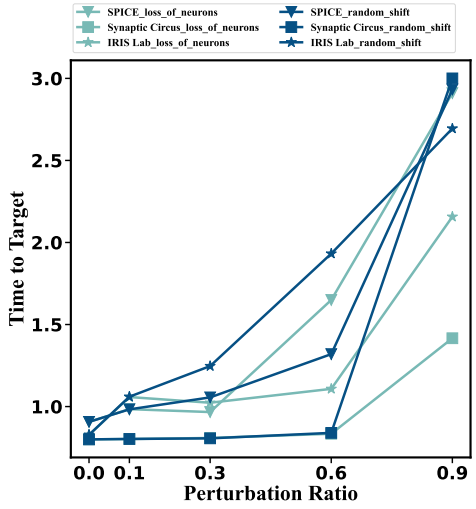


Fig. 2: The Pareto plot for the model performance of four teams in terms of the resource requirement vs. average time-to-target for Track 1. (a) The computation requirement vs. average time-to-target. (b) The memory requirement vs. average time-to-target.

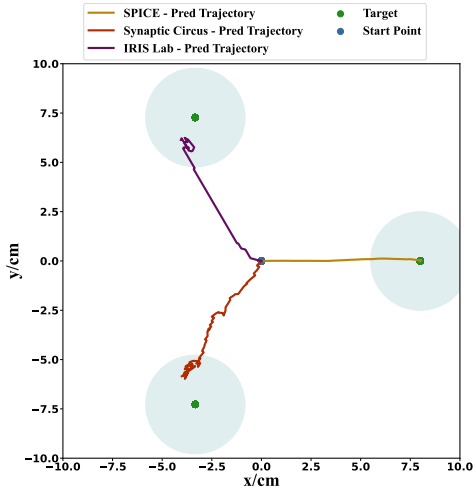
B. Team SPICE

Khaleelulla Khan Nazeer et al. [23] from the Technische Universitat Dresden and the Centre for Tactile Internet with Human-in-the-Loop (CeTI) won second place in this contest. In their work, they projected the input to a lower 4-dimensional space before passing it to a recurrent layer to track signal dynamics. To further improve efficiency, the Event-based Gated Recurrent Unit (EGRU) is employed as the recurrent network to exploit the temporal sparsity of neural signals while minimizing active computations, thereby enhancing the energy efficiency of closed-loop neural decoding within implantable BMI systems. Besides, they integrated EGRUs into reinforcement learning (RL) for neural decoding and proposed a reward function to provide a smooth, differentiable signal for reaching a target. The training of their model was conducted both in

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(a)



(b)

Fig. 3: The results from three teams for perturbations experiments in Track 2 of the closed-loop system. (a) The average time-to-target vs. perturbation ratio. (b) The trajectory for teams in a perturbation ratio of 0.3.

open-loop pre-training and closed-loop RL with perturbations to enhance the robustness. Their results demonstrate a high level of performance, as they achieved an average time-to-target of approximately 0.9 seconds in the perturbation-free task, utilizing about 2k parameters, while the results of perturbation experiments are represented in the Table II.

C. Team IRIS Lab

Chanwook Hwang et al. [24] from the Sungkyunkwan University won third place in this contest. They proposed three strategies for closed-loop decoding: Reinforcement learning (RL), Random-Step (RS), and Episode-Based (EP). A well-designed reward function is utilized in the RL algorithm to

TABLE II: Summary of performance of winning teams in Track 2 (LN: loss of Neurons, ES: Electrode Shift)

Team Name			Synaptic Circus (Linear Model)		SPICE		IRIS Lab	
Perturb Type			LN	ES	LN	ES	LN	ES
Ratio	0.0	Ave Time	0.8	0.8	0.91	0.91	0.83	0.83
		Footprint (k)	0.78	0.78	2.17	2.17	6.14	6.14
		MACs (k)	0	0	4.14	4.14	0	0
		ACs (k)	0.62	0.62	5.7	5.7	31.1	31.1
	0.1	Ave Time	0.8	0.8	0.98	0.98	1.05	1.06
		Footprint (k)	0.78	0.78	2.17	2.17	6.14	6.14
		MACs (k)	0	0	4.45	4.45	0	0
		ACs (k)	0.54	0.68	7.16	7.98	33.39	35.61
	0.6	Ave Time	0.83	0.84	1.65	1.32	1.11	1.93
		Footprint (k)	0.78	0.78	2.17	2.17	6.14	6.14
		MACs (k)	0	0	7.57	6.03	0	0
		ACs (k)	0.49	1.33	6.04	12.0	23.38	74.92

guide the decoder to generate velocity vectors aligned with the direction toward the target. RS and EP are combined as a two-phase training approach, enabling fast training that incorporates temporal dynamics and feedback-based corrections to adapt to a dynamic closed-loop OPS environment. To enhance robustness, they also implemented Perturbation-injected training with randomly sampled zero and shift ratios. From the results demonstrated in the Table II and the Pareto plot in fig. 2, their model on the Pareto frontier achieves a good trade-off between cost and average time-to-target.

VI. Discussion and Conclusion

A total of 10 teams from 8 institutions participated in the IEEE BioCAS Grand Challenge to develop algorithms on neural decoding for motor control of non-human primates using an open-access dataset and code harness from [21]. Different from other challenges, we provide a brain simulator to enable comparing closed-loop decoding performance. We hope that this grand challenge will increase neuromorphic and neural engineering researchers' interest in developing more energy-efficient models and push the boundary for neural decoder design toward next-generation BMI systems. The challenge has also provided us insight into how to improve the brain-model for future iterations of the closed-loop decoding challenge.

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