Mapping the Interdisciplinary Landscape of Neuroscience and Engineering: A Two-Stage Interaction Framework

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***Abstract*—This paper introduces a structured framework to understand the interdisciplinary relationship between neuroscience and engineering. It proposes two distinct but interconnected stages of interaction: (1) engineering-driven applications, where engineering tools facilitate the study and manipulation of neural processes, and (2) biology-driven innovation, where principles from neuroscience inspire the development of novel engineering systems. Through a review of recent research and technology, the study elucidates how these bidirectional influences co-evolve, fostering progress in areas ranging from neural data acquisition to neuromorphic computing. This framework not only clarifies the mutual influence of these fields but also highlights opportunities for future cross-disciplinary collaborations.**

I. Engineering-Driven Interactions

The first stage of interaction, engineering-driven applications, centers on the development and implementation of engineering solutions to address challenges in neuroscience. This stage is defined by the use of engineering tools, computational techniques, and novel sensing and stimulation devices. Rather than primarily drawing from biological insights, it adopts an engineering mindset: designing technologies that enhance our ability to study and interact with the brain.

A prominent example is the development of deep brain–machine interfaces (DBMIs), which translate neural activity into measurable digital signals and also provide an option of utilizing them as control signals for external devices. These systems rely on advancements in electrical engineering, signal processing, and machine learning to interface with deep brain structures such as the basal ganglia, thalamus, and hippocampus. Progress in this area is essential for advancing both neuroscience research and its clinical applications.

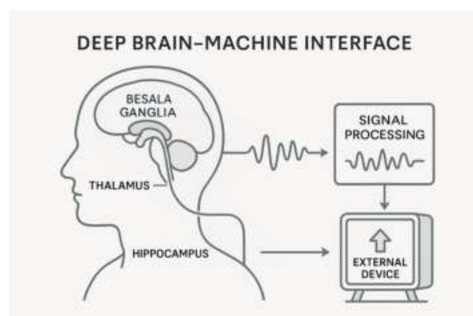

Figure 1. Deep brain–machine interface illustrating signal acquisition from deep brain structures, processing, and control of an external device.

Figure 1 illustrates how implanted microelectrodes in deep brain regions—the basal ganglia, thalamus, and hippocampus—record neuronal voltage fluctuations that are routed to a signal-processing unit. There, the signals are decoded into control commands and sent to an external device, enabling real-time translation of the user's intentions into action, with feedback loops continuously refining performance over time.

To illustrate the variety of devices used in this stage, we compare three examples. The HH128 device, produced by SpikeGadgets, was used by Kleinman, M. R., & Foster, D. J. (2024) [1] to record electrophysiological activity from the dorsal CA1 in freely behaving rats to gather spatial and navigational information. In contrast, Tara O'Driscoll (2023) [2] employed the MouseLog-16C for wireless recordings of head direction cells in the anterodorsal thalamic nucleus (ADN) of developing rat pups. This setup enabled natural-environment recordings and minimized sensory disruption while studying early spatial cell development. Furthermore, Kendall-Bar et al. (2023) [3] used the Evolocus Neurologger 3 in a custom submersible system to record EEG and ECG data from free-ranging northern elephant seals. This allowed the identification of underwater sleep patterns and the development of a sleep-scape map of elephant seals in the North Pacific.

An important advancement of DBMIs is their shift from traditional brain–machine interfaces (BMIs), which primarily focus on cortical decoding—the extraction of information from cerebral cortex activity. In contrast, DBMIs target subcortical structures that are critical for cognition, emotion, and essential life functions. The HH128, MouseLog-16C, and Neurologger 3 can all be considered DBMIs, as they record from or stimulate deep brain structures such as the basal ganglia, limbic system, diencephalon, brainstem, hippocampus, and cerebellum. Traditional BMIs, however, are typically limited to the cortical surface.

The transition from BMIs to DBMIs illustrates the growing contribution of engineering in data collection and neural region stimulation. With these interdisciplinary advancements, DBMIs aim to restore lost functions, suppress pathological activity, and modulate mood and cognition. They can repair, enhance, or reprogram malfunctioning brain circuits associated with neurological and psychiatric disorders. As Sui et al. (2022) [4] note, "DBS is a successful interface for the clinical treatment of many neurological and psychiatric disorders... Parkinson's disease, essential tremor, and dystonia... Other disorders such as epilepsy and Alzheimer's disease have become new frontiers for DBS applications."

Machine learning, especially deep learning, has become a key part of engineering-driven brain–machine interfaces (BMIs). In the past, these systems depended on manually selected features from brain signals, which made them hard to generalize and required long setup times. Today, deep learning models like EEGNet can automatically learn important patterns in the data without needing handcrafted features, making them more flexible and easier to use across different people and situations (Ferrero et al., 2024) [5].

For example, as summarized in figure 2, Ferrero et al. (2024) [5] used a deep learning approach to control a robotic exoskeleton using brain signals. They trained their model on data from many people, then quickly adapted it for each individual user. This helped reduce the time needed for calibration while keeping the system accurate and responsive. In another study, Khademi et al. (2023) [6] showed how deep learning can improve BMI systems by better detecting the user's motor intentions and reducing the need for manual tuning. As BMIs continue to develop, machine learning will play an increasingly important role in making them more reliable, faster to use, and better suited for real-world applications.

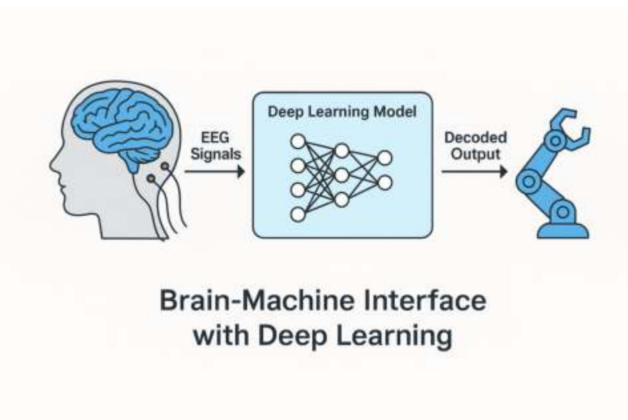

Figure 2. EEG-based Brain-Machine Interface using deep learning to control a robotic arm.

II. Biology-Driven Interactions

The second stage of interaction is biology-driven, where engineering applications are inspired by biological insights. In this stage, neural mechanisms inform the design of algorithms and control systems, enabling machines to simulate cognitive and adaptive behaviors to solve a multitude of computationally complex problem efficiently. These systems especially aim to mimic the extreme energy efficiency and self directness of the natural neurons. To illustrate this process, we conducted a literature survey highlighting key examples of biologically inspired engineering models.

One such example is the development of Bio-GWM, a biologically inspired learning interface modeled after cognitive control and memory updating mechanisms of the human prefrontal cortex and basal ganglia (Zhang et al., 2024) [7]. These neural functions are translated into learning rules that allow machines to perform instructed vision tasks with increased flexibility and contextual awareness.

Similarly, Arena et al. (2008) [8] demonstrated how insect locomotion and neural control systems can inform robotic movement. Their study integrated biologically inspired components such as Spiking Neural Networks (SNNs), Central Pattern Generators (CPGs), and modular design principles. SNNs replicate the way biological neurons communicate via discrete spikes, facilitating event-driven computation that mirrors real neural processing. CPGs model rhythmic neural circuits responsible for actions like walking or swimming, enabling adaptive locomotion without continuous sensory input. Finally, modular neural control allows each leg of the robot to function semi-autonomously while maintaining coordinated motion—enhancing robustness and fault tolerance.

While some biologically inspired models are primarily intuitive or structural, others incorporate learning processes that mimic how the brain adapts to stimuli. Mostafa, Salama, and Wahbah (2023) [9] describe SNNs that learn via spike-timing-dependent plasticity (STDP)—a biologically plausible

mechanism where synaptic strength is adjusted based on the timing of spikes between neurons. This allows SNNs to learn in real time, closely emulating the way the brain forms and strengthens associations.
Another critical consideration in biology-driven models is the trade-off between complexity and computational efficiency. Lightweight models offer faster decision-making and predictability, while more complex models provide greater adaptability and generalizability in uncertain environments. For example, Sánchez et al. (2021) [10] showed that incorporating adaptive thresholding, STDP, and homeostatic regulation—features that increase biological fidelity—enhances the learning capability and robustness of SNNs. However, these benefits come with increased computational costs, illustrating the balance between model performance and efficiency.

Interaction Stage	Key Example	Core Concept	Discipline Leveraged
Engineering-Driven	Deep Brain–Machine Interfaces (DBMIs)	Neural data acquisition & control	Electrical engineering, AI
Engineering-Driven	EEGNet + Exoskeleton	Calibration-light brain decoding	Deep learning, signal processing
Biology-Driven	Bio-GWM	Cognitive control for flexible learning	Neuroscience, computer vision
Biology-Driven	SNN + CPGs + modular robotics	Rhythmic, adaptive locomotion	Biology, robotics

Table I. This table highlights how engineering aids neuroscience (top two rows) and how neural principles inspire technology (bottom two rows).

III. Conclusion

The relationship between neuroscience and engineering is not unidirectional but co-evolutionary. Table 1 provides an overview of the two-stage framework to classify and analyze the interdisciplinary interactions between these fields. The first stage—engineering-driven applications—emphasizes the development of tools such as the HH128, MouseLog-16C, and Evolocus Neurologger 3, which enable more precise observation and modulation of neural activity. The transition from traditional BMIs to DBMIs reflects engineering's expanding role in clinical and research settings, particularly in addressing neurological and psychiatric disorders.
The second stage—biology-driven applications—demonstrates how insights from neural systems inspire engineering innovations. From event-based learning mechanisms in SNNs to biologically structured robotic control systems, this stage shows how closely biological function can be mapped onto artificial systems. These models not only replicate neural behavior but also introduce novel ways to solve engineering problems.
Together, these two stages underscore the dynamic and reciprocal relationship between neuroscience and engineering. By continuing to integrate these disciplines, researchers can expect to make substantial advancements in neurotechnology, robotics, medicine, and artificial intelligence. As the boundaries between biological and artificial systems continue to blur, fostering effective interdisciplinary collaboration becomes increasingly essential.

References

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