Energy-efficient Neuromorphic Computing in Light of the Structural and Functional Evolution of Multi-scale Insect Brains

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Metrics of brain complexity scale *hypometrically* with body size; an insect twice as large as another will, on average, have a brain that is *less* than twice as large. Debate continues on the origins of hypometric scaling (which appears to be universal), but the pattern suggests that although more computational resources may be necessary with larger and more complex sensory and motor systems, the marginal amount of computational resources necessary to achieve larger scale diminishes as organisms get larger. In reverse, as organisms evolve smaller body sizes more of their computational resources are conserved. So, natural systems increase their relative computational footprint – devoting proportionally more developmental as well as energetic resources to computation – at smaller scales. A detailed understanding of this shift in may be important for the miniaturization of engineered systems.

Therefore, we studied smaller-scale changes across the brain with evolution of small body size using a multi-species lineage of bees. These species differ by over two orders of magnitude in body mass, yet brain volume scaled hypometrically, with the smallest bees having proportionally larger brains. One hypothesis was that central processing would be discounted in smaller bees in favor of shifting investment into peripheral processing –like recent advances in computer architecture favoring increased sophistication toward the periphery. In contrast, we found that central areas involved in information processing were proportionally much larger in smaller bees while some sensory areas involved in feature extraction scaled similarly or isometrically. These results indicate that smaller species' ***central*** **computational resources receive proportionally additional investment relative to larger species**. Additionally, it is possible that the **energetic demands** of change with size, as in vertebrates. Analogously, changing the clock rate of engineering components may increase performance (and energetic demands) without making changes in the components themselves. We measured the concentration of two key proteins related to brain energy turnover. These did not differ across size, suggesting that **the device-level neuronal characteristics of brains were similar across sizes. However, greater energy turnover in smaller brains, as in vertebrates, would suggest that the catalytic reaction rates per protein are higher in smaller brains, like computing components running at higher clock speeds.**

Therefore, miniaturized brains achieve high performance by shifting relative investment in sensory and central processing. Thus, nature-inspired innovation should be focused on brain-scale architectures reflecting information-processing challenges as opposed to small-scale changes in neuronal mechanisms. Accordingly, we developed an insect-inspired neural network architecture for central processing (Figure 1; Hong and Pavlic, 2021) showing that structural randomization can create a **general-purpose central processing resource** that **would be conserved at small scales** and **re-used by regions of the scaled down brains**. We have also shown that **feature-extraction systems** are **dynamic and generate efficient, low-order representations of complex environmental features**. We mimicked this dynamic encoding (Li et al, 2020; Li and Cao, 2020) using graph convolutional network models with reinforcement learning that tunes these codes over learning epochs. The major lesson from this project is that small-scale computation can benefit from **randomization**, **inhibitory plasticity**, and **feedback** for self-tuning.

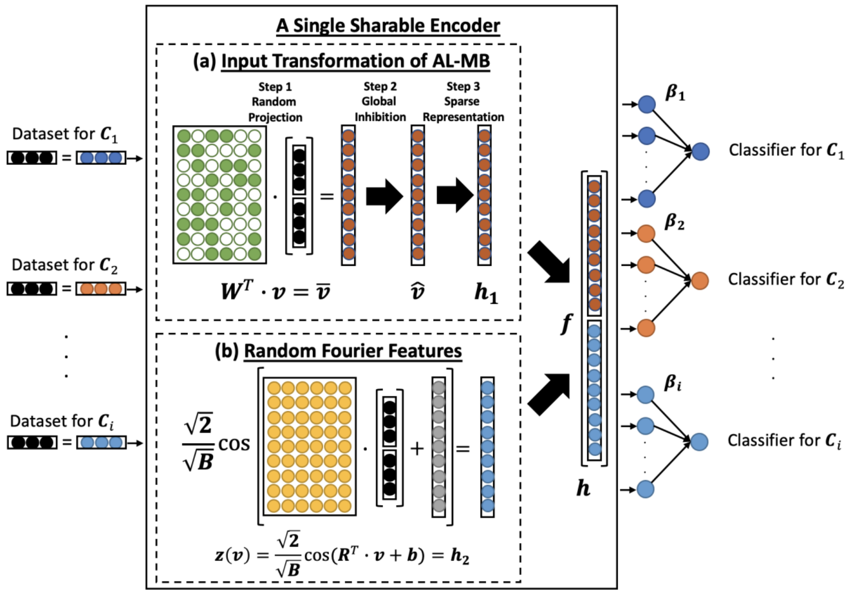

Figure 1: Insect-inspired central-processing architecture for higher-order relational learning from Hong and Pavlic (2021). Randomized AL–MB projections between the antennal lobe (AL) and mushroom body (MB) neural-network analogs create a shared central resource that pre-processes sensory input and can be used by other regions of the brain, allowing them to scale down while it is conserved.

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