**Embodied (4EA) Cognitive Computational Neuroscience**

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Abstract: I argue that ideas and models about the mechanisms of neural computation and representation—including computational architecture, representational format, encoding schemes, learning methods, computation-representation coordination, and substrate-dependent aspects—must be tested by studying embodied neural systems. Thus, cognitive computational neuroscience—the study of neural computations over neural representations—must be an embodied research program.

Keywords: mechanism, computation, representation, embodiment, 4EA, explanation

I agree with Mougenot and Matheson (2024) that cognitive neuroscience can be integrated with embodied approaches by searching for multilevel mechanistic explanations that span the brain, body, and environment. The result is *embodied cognitive neuroscience*.

They cite several models, some of which involve computational modeling. Yet Mougenot and Matheson write that “whether our arguments apply [to] computational modeling … is beyond the scope of the present argument”. I will extend their argument to computational neuroscience, that is, the study of neural computation and representation via mathematical and computational modeling. I follow Mougenot and Matheson in understanding “embodied” broadly to include all 4EA: embodied, embedded, extended, enactive, and affective cognition approaches.

In previous work, I argued that neural representations must be understood within an embodied framework (Piccinini 2022) and that cognitive computational neuroscience is committed to multilevel mechanistic explanation (Ritchie and Piccinini 2024). Here I aim to briefly clarify why and how neural computations and representations fit within an embodied mechanistic framework. The result is embodied cognitive *computational* neuroscience.

One apparent obstacle to integrating neural computation and representation with an embodied (4EA) approach is that computation and representation are substrate independent, that is, they are defined in terms that do not depend on properties that are specific to their physical substrate. Instead, computation is defined in terms of degrees of freedom, and representation is defined in terms of guiding behavior with respect to target environmental variables (cf. Anderson and Piccinini 2024).

Yet it would be a mistake to infer from substrate independence in this sense that computation and representation are purely “functional” (as opposed to structural, or mechanistic) notions, which are independent of structural or mechanistic aspects of their physical substrate. A related mistake would be to conclude that the study of neural computation and representation is autonomous from the study of neural mechanisms. In the other direction, it would be a mistake to conclude that, since cognition is embodied, there is no such thing as neural computation or representation.

In fact, the following are among several intertwined aspects of neural computation and representation that are both mechanistic and embodied (in a broad sense):

1. Computational architecture. Different computing systems are made of different sorts of components organized in different ways. For instance, ordinary digital computers rely on digital processors coordinated with memory registers, and general-purpose analog computers (GPACs) rely on integrators that can integrate continuous variables. In contrast, neurocomputational systems are made of biological neurons. Typical neurons combine integration performed by dendritic trees over their many inputs (which are typically discrete but received over continuous time) with a mechanism in the soma that generates action potentials only once a certain threshold is reached. Despite some partial similarities, neurons are very different from either digital processors or GPAC integrators (Piccinini and Bahar 2013). Further disanalogies include that neurons can not only excite but also inhibit one another and that neurocomputational operations are subject to many modulating factors.
2. Representational formats. Different computational architectures use different formats (cf. Coelho Mollo and Vernazzani 2023). For instance, ordinary digital computers process strings of digits (roughly, discrete states concatenated together), while GPACs typically process continuous variables. In contrast, neural systems process individual spikes, spike trains, and complex pluralities of spikes and spike trains.
3. Encoding schemes. Different representational systems encode information in different ways. For instance, ordinary digital codes such as the decimal number system encode numerical information, in part, based on the position of a digit within a string (e.g., the rightmost digit represents units, the next digit to the left represents tens, the next represents hundreds, etc.), while typical analog codes encode information using a scaled continuous variable. In contrast, neural systems encode information using features that include physical location, connection strength (between neurons), firing rate and timing, patterns of activation within a neuronal population, and dynamical evolution of the activation patterns.
4. Learning methods. Conventional computing systems have a fixed architecture, so that any learning involves changes in software not hardware. In contrast, neurocomputational systems have an architecture that changes through various learning processes at various temporal scales. While many learning schemes have been devised to approximate the results of biological learning (e.g., backpropagation, reinforcement learning) and some of them may well shed light on some aspects of biological learning, many aspects of biological learning (e.g., continual learning, learning within the real world rather than using labeled data or artificial environments) are still poorly understood.
5. Coordination between computation and representation. Conventional computing systems work in part thanks to humans who match appropriate computations to the content of the representations. For instance, a programmer might write code that correctly derives *q* (as opposed to, say, *p*, or $\rightarrow $) from *p* and *p*$\rightarrow $*q*. But a brain needs to coordinate computations and representations by itself, by learning representations and computations that are appropriate for one another. Probably this requires using extensive feedback from the body and environment while learning.
6. Substrate-dependent aspects of computation and representation. In addition to their substrate-independent aspects, computation and representation also have substrate-dependent aspects. In nervous systems, these include chemically different signaling molecules, processing speed, energy requirements, and heat dissipation (cf. Kirkpatrick 2022; Thagard 2022). By definition, these aspects of neural computation and representation depend on properties specific to the body in interaction with its environment.

Building mathematical and computational models can help develop ideas about all of the above multilevel mechanistic aspects of neural computation and representation. But the only way to test such ideas and resulting models is to investigate actual neural systems at different scales as they operate within their body and environment. Thus, cognitive computational neuroscience—the study of neural computations over neural representations—must be an embodied, mechanistic research program.

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