Introduction to Computational Neuroscience

Abstract

Computational neuroscience is an interdisciplinary field using mathematical modeling and computer simulation to understand how the brain works and how it processes information. With the combination of concepts applied on the fields of neuroscience, computer science and physics, researchers develop models that take into account many levels, including the effects of ion channels of individual neurons and macro brain systems. Classic contributions provide a biophysically detailed description of neural excitability, whereas more general theories are useful in the study of large neural ensembles. In general, the profession strives to synchronise empirical neural evidence and the theoretical awareness of psychological phenomenon including learning, memory and decision-making. The most significant ones are decoding the neural signal, neurological disorder modelling, brain-machine interface development and the improvement of both the basic questions in neuroscience and the clinical practice.

Breif Introduction

Computational neuroscience is an interdisciplinary field that unifies neuroscience, mathematics, computer science and physics to build models to explain the processes of how a neural system processes information, how the brain works, and how it behaves. By using computational simulations and mathematical formalism to address empirical findings on neural activity and hypothesis concerning the neural activity, investigators attempt to integrate the two set of data (Kriegeskorte & Douglas, 2018). Through hypothesis-driven simulations, these models also allow testing of how individual neurons and neural networks perform sensory encoding, occasions learning and memory formation and judgment-making, and they, also, highlight their usage in neuromorphic linguistics and researching neurological disorders.

Historical and Conceptual Foundations

Computational neuroscience as a field of research emerged during the middle of the twentieth century when theoretical models of neuronal excitability had been formulated. One of the contributions was the Hodgkin-Huxley model developed in 1952 which mathematically models the transmission of action potentials as well as its generation through distinct ion channels found in the cell that are selective to sodium and potassium transporters. The theoretical framework is a model of the neuronal membrane as an electrical network, and it considers both voltage-gated conductances of sodium ions and potassium ions, leakage current, and the membrane capacitance (Gerstner et al., 2014). It is a multiple scale field covering molecular properties of ion channels, the behavior of single neurons, large neuronal networks and brain-system dynamics. It concentrates on core issues in cognitive science such as the nature by which sensory inputs are encoded and by which the encoding is translated into behavior. Computational neuroscience exploits concepts developed in artificial intelligence to develop biologically inspired algorithms that increase our knowledge of the functioning of the brain. Prominent uses of it would involve explaining neuroscience-related conditions, enhancing brain-machine connections and improving machine-learning systems using neural-inspired designs (Churchland, 1988).

Key Models in Computational Neuroscience

Models in computational neuroscience vary in abstraction and complexity, facilitating focused analyses of neural functions.

Single-Neuron Models

The Hodgkin-Huxley Model is a conductance-based model representing the neuronal membrane as an electrical circuit. The primary equation for membrane potential V is:

$$C_m \frac{dV}{dt} = -g_{\mathrm{Na}} m^3 h (V - E_{\mathrm{Na}}) - g_{\mathrm{K}} n^4 (V - E_{\mathrm{K}}) - g_L (V - E_L) + I_{\mathrm{ext}}$$

where C_m is membrane capacitance, g_{Na}, g_k, and g_L are conductances, E_{Na}, E_K, and E_L are reversal potentials, m, h, and n are gating variables following first-order kinetics (e.g., $\frac{dm}{dt} = \alpha_m(V)(1-m) - \beta_m(V)m$), and $I_{ext}$is external current. The derivation involves applying Kirchhoff's current law to the membrane circuit and fitting parameters from voltage-clamp experiments (Gerstner et al., 2014).

Integrate-and-Fire Model, which treats neurons as leaky integrators.

The subthreshold dynamics are given by: $\tau \frac{dV}{dt} = -(V - V_0) + \frac{I_{\mathrm{ext}}}{G_{\mathrm{tot}}}$

where tau is the time constant, V_0 is resting potential, and G_{tot} is total conductance. A spike occurs when V reaches a threshold Theta, followed by a reset to V_r.

Network and Population Models

Rate-based models describe average firing rates m of neural populations via the equation: $\tau \frac{dm}{dt} = -m + F(I_{\mathrm{syn}} + I_{\mathrm{ext}} - T)$. Where F is a sigmoidal transfer function and T is the threshold (Gerstner et al., 2014). Cable theory models dendritic signal propagation with the partial differential equation: $\frac{\partial^2 V}{\partial x^2} = c_m \frac{\partial V}{\partial t} + I_{\text{ion}}$, which, when solved, yields the characteristic length constant $\lambda = \sqrt{r_m / r_a}$ from membrane r_m and axial r_a resistances.

Higher-Level Models

Inspired by biological neural networks, feedforward neural networks in artificial intelligence process inputs through layers. A basic unit computes an output $y = \sigma(w \cdot x + b)$, where sigma is a non-linear activation function (e.g., sigmoid), w is a vector of weights, x is the input vector, and b is a bias term. These architectures can represent complex, non-linear functions necessary for tasks like pattern recognition (Stanford University, n.d.).

Applications and Challenges

The applications of computational neuroscience are vast, including explaining neural states that are measured by functional MRI to characterize cognition states, simulating disease processes like epilepsy and Parkinson disease to screen the efficacy of therapy, and building elaborate brain-machine interfaces (Kriegeskorte & Douglas, 2018). However, a number of major challenges are still are apparent such as the development of computational models that are able to represent the size and complexity of the human cortex, the accurate symbolization of learning and synaptic plasticity, and the strict testing of model outcomes to the natural variance in empirical data.

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