Complexity and Quantum Information Science

The AdS/Brain Theory of Neural Signaling: Network-Neuron-Synapse-Molecule

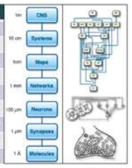
Melanie Swan PhD MBA, Research Associate, Centre for Blockchain Studies, University College London, London UK
swanm@diygenomics.org, www.melanieswan.com/ccs_poster.pdf

Quantum Information Neuroscience

Quantum information science (the multidisciplinary foundation of quantum computing) offers new ways to formalize the study of complex systems (those that are non-linear, emergent, open, unpredictable, interdependent, self-organizing, and multiscalar). Quantum computing shows promise as a platform for modeling one of the most complex systems known, the human brain. More capacious, scalable, energy-efficient, three-dimensional models are needed as the brain spans nine orders of magnitude (Figure 1).

Figure 1. Levels of Organization in the Brain [Sterratt], (image: Sejnowski)

	Level	Size (decimal)	Size (m)	Size (m)
1	Nervous system	1	> 1 m	10^{0}
2	Subsystem	0.1	10 cm	10^{-1}
3	Neural network	0.01	1 cm	10^{-2}
4	Microcircuit	0.001	1 nm	10^{-3}
5	Neuron	0.000 1	100 μm	10^{-4}
6	Dendritic arbor	0.000 01	10 μm	10^{-5}
7	Synapse	0.000 001	1 μm	10^{-6}
8	Signaling pathway	0.000 000 001	1 nm	10^{-9}
9	Ion channel	0.000 000 000 001	1 pm	10^{-12}



With available quantum computing cloud services platforms (IBM Q 27-qubit, IonQ 32-qubit, Rigetti 19Q Acorn systems), the brain is starting to come within computational reach. From the standpoint of modern computing, the brain's estimated 86 billion neurons and 242 trillion synapses are not big numbers [Martins] (Figure 2). Although long-term fault-tolerant quantum computing (million-qubit systems) requires error correction which is not immediately immanent [Preskill], existing NISQ (noisy intermediate-scale quantum) devices continue to grow in capacity and offer the ability to run model problems in the quantum environment.

Figure 2. Neural Entities and Quantum Computation

	Level	Estimated Size	
1	Neurons	86×10^{9}	86,000,000,000
2	Glia	85×10^{9}	85,000,000,000
3	Synapses	2×10^{14}	242,000,000,000,000
4	Avogadro's number	6×10^{23}	602,214,076,000,000,000,000,000
5	19 Qubits (Rigetti-available)	2^{19}	524,288
6	27 Qubits (IBM-available)	2^{27}	134,217,728
7	53 Qubits (Google-research)	2^{53}	9,007,199,254,740,990
8	79 Qubits (needed at CERN LHC)	2^{79}	604,462,909,807,315,000,000,000

From the landmark completion of the fruit fly connectome (wiring diagram) in 2018, it is clear that to complete the human connectome (and even the mouse connectome [Abbott]), a qualitatively different mode of computing is likely necessary. This would be similar to the technology-driven inflection point in the sequencing of the human genome that allowed its completion in 2001. The imaging, data processing, and storage requirements may be 1 zettabyte per human connectome [Lichtman], which compares to 59 zettabytes of data generated worldwide in 2020 [Reinsel]. Quantum computing may be precisely the computational platform that is adequate to the study of complexity of the brain (Figure 3).

Figure 3. Estimated Neurons and Synapses by Organism [Abbott]

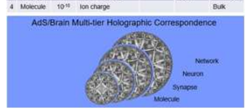
	Neurons	Synapses	Ratio	Volume	Complete
Worm	302	7,500	25	5×10^{4}	1992
Fly	100,000	10,000,000	100	5×10^{7}	2018
Mouse	71,000,000	100,000,000,000	1,408	5×10^{11}	NA
Human	86,000,000,000	242,000,000,000,000	2,814	5×10^{14}	NA

AdS/Brain Theory of Neural Signaling

The AdS/CFT (Anti-de Sitter Space/Conformal Field Theory) correspondence is the theory that any physical system with a bulk volume can be described by a boundary theory in one less dimension [Maldacena]. Neural signaling is an orchestration process between brain networks, neurons, synapses, and molecules. At the network level, the brain coordinates local and long-distance signals between gray matter and white matter. The outer layer of the cortex is gray matter (so-called due to the density of cell bodies), which contains the synapses, dendrites, and axons that form the neural circuits that process information. The inner layer is white matter, the deep subcortical regions of heavily myelinated axons that undertake the core processing of the brain. The AdS/Brain theory is the first multi-tier interpretation of the AdS/CFT correspondence, with four bulk-boundary pairs at the tiers of brain network, neuron, synapse, and molecule [Swan] (Figure 4).

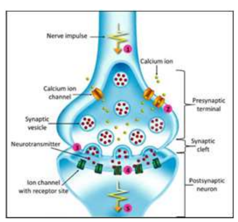
Figure 4. AdS/Brain Theory of Neural Signaling

	Tier	Scale	Signal	AdS/Brain		
1	Network	10^{-2}	Local field potential	Boundary		
2	Neuron	10^{-4}	Action potential	Bulk	Boundary	
3	Synapse	10^{-6}	Dendritic spike		Bulk	Boundary
4	Molecule	10^{-10}	Ion charge			Bulk



Chemical synapses coordinate the brain's neural signaling process between outgoing axon, presynaptic terminal, synaptic cleft, postsynaptic density, and dendritic spikes to the receiving neuron's soma (cell body) (Figure 5). From a signal-processing perspective, electrical signals from the outgoing action potential are converted to chemical signals in the presynaptic terminal, cross the synaptic cleft as neurotransmitters, are received as molecules at dendritic arbors, and are then reconverted to electrical signals as dendritic spikes on the way to the receiving neuron's center.

Figure 5. Neural Signaling in the Human Brain (image: Okinawa Institute of Science and Technology)



Electrical Signaling (Axon)
Mathematics: ODE (Ordinary Differential Equation: one unknown)

Electrical-Chemical Signaling
Mathematics: PDE (Partial Differential Equation: multiple unknowns)

Synaptic Integration
Mathematics: PDE (Partial Differential Equation: multiple unknowns)

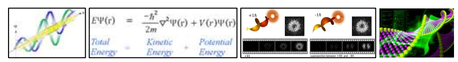
	Scale	Number	Size	Size (m)	NEURON	Microscopy
1	Neuron	86 bn	100 μm	10^{-4}	ODE	Electron
2	Synapse	242 tn	1 μm	10^{-6}	ODE	Electron/Light field
3	Signaling pathway	unknown	1 nm	10^{-9}	PDE	Light sheet
4	Ion channel	unknown	1 pm	10^{-12}	PDE	Light sheet

The two central problems in neural signaling are synaptic integration (aggregating thousands of incoming spikes from dendrites and other neurons) and electrical-chemical transmission (incorporating neuron-glia interactions at the molecular scale). These problems are addressed in the AdS/Brain theory through wavefunctions, tensor networks, and neural field theories.

1. Wavefunctions

Quantum mechanics is implicated as brain waves are central to the study of the brain, both electrical waves (action potentials, dendritic spikes) and chemical waves (astrocyte calcium signaling and neurotransmitter propagation). The wavefunction is the description of the quantum state of a system, computed (per the Schrödinger equation) as total energy (kinetic (movement) energy + potential (resting) energy)) (Figure 6). The wavefunction is complicated as it measures the positions or speeds (momenta) of complete system configurations, not merely individual particles in the system. Although electrical waves (from EEG, CT, and PET scans) have long been analyzed with solvable nonlinear wave models [Nunez], a broader implementation of quantum-mechanical wavefunctions is now available for the study of electrical and chemical brain waves.

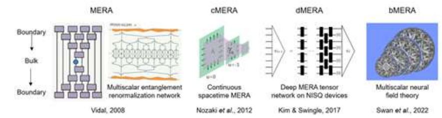
Figure 6. Schrödinger Wave Equation and Photon Orbital Angular Momentum [Erhard]



2. bMERA Tensor Networks (brain MERA)

Complex systems are often multiscalar in terms of space, time, and dynamics. Renormalization, the ability to examine a system at different scales, is important in the treatment of multiscalar systems. Various renormalization methods are applied to extract the relevant features in a system to integrate degrees-of-freedom (parameters) as the system is rolled-up to higher levels of abstraction. Renormalization is often applied by using tensor networks to represent quantum states (quantum states are high-dimensional data that can be represented by tensors) (Figure 7).

Figure 7. MERA Tensor Network Formulations (Renormalized Entanglement)

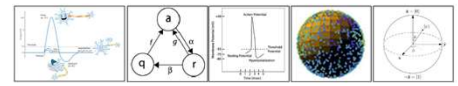


A higher-order tensor (a tensor with a large number of indices) is factored into a set of lower-order tensors whose indices can be summed (contracted) in the form of a network. This is used to renormalize entanglement (central to quantum systems) across scale tiers. A standard tool for renormalizing entanglement in quantum systems is the MERA tensor network (multi-scale entanglement renormalization ansatz) [Vidal]. For the AdS/Brain theory, a bMERA (brain MERA) version is proposed to attend to the specifics of neural field theory systems. The proposal is in line with other specific implementations of MERA (cMERA: continuous spacetime MERA and dMERA: deep learning network MERA).

3. Neural Field Theories

Large-scale collective neural activity is analyzed with neural ensemble models (small groups of neurons with uncorrelated states), neural mass models (large-scale populations of interacting neurons) and neural field theories (whole brain activity). Per empirical data, neural ensemble models produce known statistical distributions (the dynamics can be modeled with Fokker-Planck equations), but neural mass and neural field theories do not [Breakspear]. The dynamics are therefore modeled with quantum mechanical methods. Data are instantiated in superposition as the quantum information representation of all possible system states simultaneously. Two and three-state (quiescent, firing; quiescent, active, resting) models are applied [Basieva, Buice] (Figure 8).

Figure 8. Two-state and Three-state Neural Signaling Model sand Superpositioned Data



The traditional method of quantum system evolution is through Schrödinger and Heisenberg dynamics. However, the Heisenberg equation of motion is only a general approximation of movement and does not include temperature, and the Schrödinger wavefunction is limited to describing pure quantum states as opposed to mixed (subsystem) states. Thus, the AdS/Brain theory incorporates contemporary methods for quantum system evolution, namely ladder operators (raising and lowering a system) and quantum master equations (describing the time evolution of a system as a probabilistic combination of states); the simplest form is the Lindblad equation (Lindbladian), a quantum Markov model (stochastics with quantum probability). These kinds of methods indicate that whereas epileptic seizure can be explained by chaotic neural dynamics, normal resting states are more complicated, and are perhaps explained by bifurcation neural dynamics, in which there is an orbit-based organizing parameter periodically interrupted by countersignals to trigger a neural signal [Coombes].

Conclusion

Quantum information science might be used to model complexity, here in the specific example of quantum neuroscience and the AdS/Brain theory which engages wavefunctions, bMERA tensor networks, and neural field theories. New platforms such as quantum computing are needed to tackle a next level in the study of complex systems that has not been methodologically available previously. In this example, quantum computing is needed to address the human brain with complexity spanning nine orders-of-magnitude scale tiers, provide a new technology platform for connectome research, and because computational neuroscience problems require partial differential equation mathematics. There are many risks with an early stage technology such as quantum computing but overall quantum information science suggests an important research frontier for the continued study of complexity.

References

Abbott, L.F., Bock, D.D., Callaway, E.M. *et al.* (2020). The Mind of a Mouse. *Cell.* 182(6):1372-76.
Basieva, I., Khrennikov, A. & Ozawa, M. (2021). Quantum-like modeling in biology. *BioSystems.* 201:104328.
Breakspear, M. (2017). Dynamic models of large-scale brain activity. *Nat. Neurosci.* 20:340–52.
Buice, M.A. & Cowan, J.D. (2009). Statistical mechanics of the neocortex. *Prog. Biophys. Mol. Biol.* 99:53-86.
Coombes, S. & Byrne, A. (2019). Next generation neural mass models. *Nonlinear Dynamics in Computational Neuroscience* London: Springer.
Erhard, M., Krenn, M. & Zeilinger, A. (2020). Advances in high dimensional quantum entanglement. *Nat. Rev. Phys.* 2:365-81.
Lichtman, J.W., Pfister, H. & Shavit, N. (2014). The big data challenges of connectomics. *Nat. Neurosci.* 17(11):1448–54.
Maldacena, J.M. (1999). The large N limit of superconformal field theories and supergravity. *Intl. J. Theor. Phys.* 38(4):1113-33.
Martins, N.R.B., Angelica, A., Chakravarthy, K. *et al.* (2019). Human brain/cloud interface. *Front Neurosci.* 13(112):1-23.
Nunez, P.L., Srinivasan, R. & Fields, R.D. (2015). EEG functional connectivity. *Clin. Neurophysiol.* 126(1):110-20.
Preskill, J. (2021). Quantum computing 40 years later. arXiv: 2106.10522.
Reinsel, D. (2020). IDC Report: Worldwide Global DataSphere Forecast, 2020-2024 (Doc US44797920).
Sejnowski, T.J. (2020). The unreasonable effectiveness of deep learning in artificial intelligence. *Proc. Natl. Acad. Sci.* 117(48):30033-38.
Sterratt, D. *et al.* (2011). *Principles of Computational Modelling in Neuroscience.* Cambridge: Cambridge University Press, Ch. 9, pp. 226–66.
Swan, M., dos Santos, R.P., Lebedev, M.A. & Witte, F. (2022). *Quantum Computing for the Brain.* London: World Scientific.
Vidal, G. (2008). Class of quantum many-body states that can be efficiently simulated. *Phys. Rev. Lett.* 101:110501.