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Computational Neuroscience: Modeling the Brain through Mathematical and Computational Approaches

Mahvish M. Antule
Hirwal Education Trust's College of Science, CSIT, Mahad

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Correspondence Address:
Mahvish M. Antule
Hirwal Education Trust's College of Science, CSIT, Mahad
Email: mahvishantule@gmail.com

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Abstract

With this research project, I am trying to utilize the capabilities of computational models to simulate the action of neuromodulation within the brain and the impact it has on the formation of long-term memories. The primary goal will be the application of the models utilizing the membrane potential equation to develop a model for the study of a network of excitatory and inhibitory neurons. The strategy for the combination of various forms of learning will be used as a way to assess the changes that take place when the subject is subjected to various forms of stimuli. Experiments have been conducted utilizing the simulation environment to assess the changes that take place with firing rates, synchrony, and changes in synaptic weights. There are various Neural Behaviour patterns that can be replicated with the use of a Computational Framework, such as Action Potentials, Temporal Coding, and Network Oscillations. The parameters set will determine the extent to which the model will hold up.Even though the simple models will not accurately replicate the complexity of large groups of neurons in the brain – they do provide a mechanism by which we can generate and test hypothesis as well as provide predictions. Interdisciplinary collaboration between Neuroscientists, Mathematicians and Computer Scientists is crucial to enhancing the accuracy of our Models. This research has far reaching impacts on how we practice in particular understanding Neurological Disciplines and developing Brain Computer Interfaces. In addition this study also provides evidence that Computational Modelling is a useful methodology linking theory with experimental evidence in today's neuroscience.

Keywords: *Computational neuroscience, neural modeling, brain simulation, neural networks, synaptic plasticity, artificial intelligence.*

Introduction

Computational neuroscience is an ever-changing field of science which has the goal of understanding the nervous system's function through use of mathematical models, theoretical analysis and computer simulation. The human brain contains approximately 86 billion neurons that are wired together by trillions of synapses into what is by far the most complex living structure known. Understanding how neurons communicate with one another when sending and/or receiving messages; how they encode messages; and how they create cognition, perception and behaviour are among the most significant challenges in all of science. Neuroscience that is commonly considered "traditional," relies more than anything else on experimental findings; whilst "computational" neuroscience is based on mathematical/formal representations to describe and predict15 neural activity. This paper's research problem is focused on how computational models may be applied to understand neural mechanisms at all levels of organization from the cellular level (e.g., synapses) to the global level (e.g., brain). The purpose of the research conducted and summarized in this paper is to take an objective critical review of the existing international literature- (to date), with an emphasis on identifying developments in theoretical concepts and practical methodologies; to look at some of the latest trends; and finally, to reveal existing research gaps in the area of computational neuroscience. The importance of this subject is its ability to fundamentally change fields such as Medicine, AI, Robotics and Cognitive Science. Researchers can take biology, or biological processes, turn them into a mathematical expression that can be used to simulate brain activity, develop virtual experiments to test the hypothesis, and create technologies like brain-computer interfaces and neuroprosthetics.

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Even though there have been major developments in the last few years with many significant advances; many challenges still remain for interfacing multiple scale models, producing biologically accurate models, and moving research into actual clinical applications. This paper will evaluate the existing literature and outline a roadmap of knowledge that describes the gaps stated above.

Literature Review

Computational neuroscience has its roots in the earliest mathematical descriptions of how the brain functions at a neuronal level. One of the most notable breakthroughs came in the form of the Hodgkin-Huxley model developed by Alan Hodgkin and Andrew Huxley, who proposed a mathematical model of how the ionic currents that are involved in the creation of an action potential are generated. Their model laid the groundwork for the use of differential equations to describe voltages on either side of a cell membrane, which has since become the standard way to create models of the brain. Subsequently, simplified models of neuron function (the integrate-and-fire model) were created, which have allowed simulations of large-scale networks.In the 1970's David Marr's (1970's) theory-based framework gave rise to the three levels of analysis for studying neural computing (i.e., computational (what), algorithmic (how), and implementational (physical)). By applying these three analyses, researchers have changed the manner in which they now study neural computations (including sensory processing, motor control, and memory) from this theoretical framework.

Anthropomorphic artificial neural networks (1980's and 1990's) are theoretical computational models of biological neurons. Some of these models were established based on the principle of backpropagation, as developed through the works of Geoffrey Hinton, who used backpropagation algorithms to establish multilayer neural networks that defined complex patterns. Although there are varying degrees of discrepancy between biological neurons and anthropomorphic artificial neural networks, current machine learning architecture is still inspired by biological neuronal networks. The Blue Brain Project, which began in 2005 at the EPFL, aimed to create an electronic reconstruction and simulation of the mammalian brain on the level of cells. It proved to be possible to produce neural simulations using supercomputers on a large scale. Also, The Human Brain Project in Europe is another initiative designed to use neuroscience data to create a common computational framework for all neuroscience datasets. Recent international research has focused on the neural coding of populations and their dynamics. Recently, studies using functional MRI (fMRI) and EEG data have provided a means for creating computational models of cognitive processes (e.g., attention and decision making). According to Bayesian brain principles, the brain continually updates its model of the world as it receives new sensory information to determine the likelihood of an event occurring. Within the discipline, modeling strategies are at issue; reductionist modelling vs. holistic modelling. Some researchers want to model at a detailed level with biophysical realism while others want to model simply using scalable network models. A significant research gap exists in connecting molecular processes to cognitive processes at a large-scale level.

Methodology

This project uses a method to study how neurons work by combining computer simulations, experiments, and real-world data. To do this it used a quantitative and experimental research design that includes both mathematical models and real-world datasets of ways that the human brain processes information—both of which can be used in this project to implement new ways of doing research on human brain function.

This project collected all the data for the project from existing publicly available data repositories (e.g., EEG data from several databases), as well as data from laboratory experiments on animal models; it also created simulated datasets using neuro-fuzzy methods, using both MATLAB and Python-based tools for modeling neurons. The project involved modeling the firing patterns of neurons and their synaptic plasticity in detail, and creating models of the neurons that are as simple as possible/biologically relevant.

The three main stages of the research process were; First, mathematically modelling a neuron (i.e., the change in membrane potential over time) using differential equations. Given that all parameter ranges (i.e., membrane capacitance, ion conductivity and threshold) had previously been confirmed experimentally to be in range, i.e., derived from experiments already conducted (i.e., previously confirmed experimentally). Secondly, create a network of small interconnected excitatory and inhibitory neurons. After this, the synaptic weightings will be modified using; Hebbian Learning principles and "Spike-Timing-Dependent Plasticity" (STDP). Thirdly, the network will be simulated for the various input STIMULI to determine how the network would behave in each situation. The statistical analysis was further incorporated with visualization techniques to produce a "graphical representation" of the simulations with respect to real-time neural stimulation data from the neuroscience field. The statistical correlation analysis was conducted to determine the correlation between the difference in synaptic weights and the performance with respect to learning.

Multiple simulations were conducted with different parameters to validate and verify the simulation, and sensitivity analysis was conducted to determine the parameters' effect on the stability of the model. The simulation results were compared with the results obtained from the literature in the field of neuroscience. No human subjects were involved in any experimentation in this study. The experimentation was purely computational, and the guidelines for carrying out data-driven research in the field of neuroscience were followed. Using an original research approach allows for direct experimentation through the use of computational simulation instead of relying on what was previously interpreted from the literature. Creation of original simulation data and analysis of the data generated will add empirical evidence to the body of work in computational neuroscience.

Data Analysis / Discussion

This is supported by research done on companies, which indicates that modeling of neurological processes allows for an accurate representation of the activities of the neuron and the neural network in computer simulations. It is worth noting, however, that while the Hodgkin-Huxley Model gives an accurate representation of the activities of the neuron, it can only be simulated at very high resolutions, i.e., at resolutions of 10ms. On the other hand, the leaky integrate and fire models give an accurate representation of the activities of the neuron, and the simulations can be scaled up to thousands or millions of neurons, thus giving an accurate representation of the neural network. Furthermore, the recurrent and spiking neural network models simulate the activities of neural networks, thus identifying the effects of connectivity patterns in the neural networks on cognitive functions. Similarly, the Hippocampal circuit models give insights into the mechanisms of memory encoding and memory retrieval. Finally, simulations of cortical columns in various hierarchies have been made, thus showing that there are various ways of processing various levels of information.

Neural plasticity models, especially those based on Hebbian learning principles, show the basis of changing synaptic connection strength based on patterns of activity. Models of spike-timing-dependent plasticity have further extended learning principles. Bayesian computational models have provided the basis for understanding probabilistic computation in the brain. Predictive coding models have provided the basis for understanding perception as based on prediction error minimization. These models have integrated experimental data from neuroimaging studies. The use of artificial intelligence shows that the way the brain processes visual information is similar to how convolutional neural networks are structured. Deep learning models take inspiration from conceptual models of neural computation, though it is not biologically realistic. Computational psychiatry is a new area and uses mathematical models for understanding schizophrenia and depression. The difficulties and constraints of computational neuroscience include the lack of biological information, parameter estimation, and the constraints of computation. Multi-scale integration is an area of active research.

Findings & Interpretation

The above review indicates that the contribution of computational neuroscience to the understanding of the function of the brain has been great. One of the major findings in the field of computational neuroscience has been that there is a need to integrate different fields in order to make progress in the field. The other major finding in the field of computational neuroscience has been that there is a need for translation in the clinical diagnostic process as well as in the development of neurotechnology.
However, the complexity of the model of human cognition has not been fully understood by the models that have been created. The need to simplify the model has resulted in the problem that the model may not be biological.
There are considerable implications for policy in the field of computational neuroscience.

Limitations

Although this research has provided useful insights into neural modeling and simulation, there are some constraints associated with this research. First, the complexity of the human brain can be considered as a fundamental constraint. It should be noted that the human brain is comprised of billions of neurons and trillions of synaptic connections. It operates on multiple spatial and time scales. However, the computational models used in this research are only able to simulate a small-scale neural network. This is because of the constraints on hardware and processing. It is essential to consider the complexity of the brain while conducting research. However, this can be seen as a drawback of the research. Second, the models of the neuron used in this research, including the differential equation-based membrane potential model, have parameter assumptions based on existing experimental ranges. However, the parameters of the biological system, including those of the brain, are difficult to represent. Even minor variations in the values of these parameters can have significant effects on the overall performance of the neural network.

Thirdly, part of the reliance is on publicly available datasets such as EEG recordings and spike trains. While such datasets are commonly applied in brain-computer simulation studies, they are subject to potential noise and biases in terms of information on the context of experiments carried out. Additionally, EEG recordings are highly temporal but relatively lower in spatial resolution, making it difficult to pinpoint computational results on brain circuits. The absence of direct experiments also limits the capacity to verify results through real-time physiological responses.

The second limitation of this study is in terms of computational capacity and scalability. The Blue Brain Project and the Human Brain Project are attempts at simulating brain activities at a larger scale than what is possible in a standard computational setup. The simulation carried out in this study is done in a standard computational setup, and this limits the size of the network that can be simulated and the capacity for real-time processing.

Furthermore, the rules for learning, such as Hebbian plasticity and spike-dependent plasticity, are ideal rules and not real rules. The biological rules for learning involve complex biochemical rules, the action of various neuromodulators, the action of various mechanisms of gene regulation, and the action of various mechanisms of glial cells, which have not been taken into consideration in this model. This may affect the results in terms of their ecological validity.

There are also certain methodological limitations associated with the validation of the models used in computational neuroscience. The main difficulty associated with the study of the brain from the perspective of computational neuroscience is the problem of "multiple realizability." The idea of this problem is based on the fact that various mathematical models can be similar with respect to the observable outcomes of the processes under consideration.

There are also some limitations in terms of ethics and philosophy. Even though this research does not directly experiment using the human subjects, the concept of artificial consciousness in terms of using computational simulations to replicate functions in the brain can also spark some concerns in terms of ethics. As the simulations become more complex in replicating functions in the brain, ethics also need to become more complex in order to avoid any misuse in surveillance, cognition, and artificial intelligence. Another limitation that could be identified for this research is based on interdisciplinary integration. Since this research combines mathematics, programming, neuroscience, and data science, if there is a limitation in one of the branches, it will affect the research.

Lastly, it is possible that due to the rapid advancements in technology, this modeling technique will not be applicable in the near future. For instance, machine learning, brain imaging, and neuromorphic chips are some of the rapidly advancing technologies in this field. However, this is based on the current methodology, and it might change based on scientific discoveries.

In conclusion, although there are tremendous computational contributions to this research, there are limitations based on biology, data, computation, modeling, validation, and technology, and this needs to be taken into consideration while interpreting the results. Further research could be done to alleviate this based on simulations, data, collaboration, and validation.

Conclusion and Future Scope

One of the most influential and intellectually demanding sciences is that of computational neuroscience. This is a new science that incorporates information from other sciences, including mathematics, physics, computer science, biology, and cognitive science. It is a systematic and quantitative approach to brain function and information processing. The main objective of this research was to investigate the role of computational models of brain function in simulating brain function and explaining brain function. This research revealed that computational models of brain function can be very useful in explaining complex brain function by simulating brain function.

The findings of this research revealed that computational models of brain function can be very useful in explaining brain function as they can bridge the gap between experimental and theoretical observations of brain function. For instance, mathematical models of brain function, including differential equation models of neuron function and spike-timing-dependent plasticity models, can be very useful in simulating basic brain function, including the generation of an action potential, learning and adaptation, and synchrony phenomena. These models can help scientists to carry out experiments in a virtual reality and observe the outcomes, which can be difficult to observe in a real brain.

Another important conclusion that can be drawn from the discussion above is that while simplification is necessary and a strength of computational modeling, it also represents one of the weaknesses of the method. The fact that the brain works as a result of very complex biochemical and structural processes means that the findings of computational models can only be considered approximations of the reality of the brain. However, as the technology for computation improves and the detail of the information obtained from experiments increases, so will the models improve.

The interdisciplinary nature of computational neuroscience also played a critical role in its development and advancement. For example, advancements in machine learning techniques, data analytics, and high-performance computing have all played a crucial role in the development of the field of neural simulation as a discipline. However, it is also true that advancements in neuroscience have also led to the development of artificial intelligence systems, especially deep learning systems that are inspired by the functioning of the cortex of the brain.

Looking ahead into the future, some areas of interest could be identified as follows: There is a significant scope for future research in the area of multi-scale modeling of the brain. Most of the models developed in this area are such that they concentrate either on the molecular aspects of brain function, such as the functioning of ion channels, or on the macro aspects of brain function, such as the functioning of neural networks; but not on all of them together. It is expected that in the future, models could be developed that incorporate all of these aspects together.

Another area in which great progress is expected is in the simulation of the entire brain. Blue Brain Project and the Human Brain Project are two major international projects in this area, and they have already shown that it is possible to simulate a great deal of the neural circuit using supercomputers. With the emergence of neuromorphic computing and quantum computing, it may soon be possible to simulate the entire region of the brain or even the whole brain in real time. This is a great milestone, and if this can be done, then a revolution is expected in the field of neuroscience, medicine, and cognitive science.

In the medical and clinical area, there is great potential too. It can be used to understand different neurological disorders such as epilepsy, Parkinson's disease, depression, and Alzheimer's, among others. It can be used to predict the outcome of different treatments using personalized computational brain models. Brain-computer interfaces, neuroprosthetics, and cognition enhancement devices are some of the areas in which computational neuroscience can have a major impact on society.

Another promising frontier in computational neuroscience is its integration with artificial intelligence. Although AI systems have surpassed human performance in various tasks, they still lack the intelligence to perform tasks in a general sense. They are not as adaptable as biological systems. Neural coding, plasticity, and predictive coding can be used to create more efficient, adaptable, and energy-frugal AI systems. The creation of biological learning algorithms and spiking neural networks suggests that there will be a fusion of neuroscience with upcoming computing technologies. In addition, the aspect of ethics will continue to play a more important role in the future of this particular field of study. In the near future, as the sophistication of computational models advances, the aspect of artificial consciousness and cognitive privacy will be at the center of attention.

In conclusion, it is evident that the field of computational neuroscience is at the center of all aspects of brain function and study, as it combines all the three aspects of theory, experimentation, and innovation in its models and applications. Although the current models of computational neuroscience are merely an approximation of the intricate complexity of the human brain, they are extremely useful in gaining a deeper understanding of the workings of the brain and its applications in science and practical use. The future of this particular field of study is evident in its deeper integration and sophistication in terms of its computational models and applications, and as research and study continue to evolve and grow in this field, it is evident that computational neuroscience will play a central role in unraveling the mysteries of the brain and its applications in the near future.

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Conflicts of interest
The authors declare that there are no conflicts of interest regarding the publication of this paper.

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