Quantum Wave Function for Information-Processing

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Abstract

McCulloch and Pitts first proposed a mathematical model of a neuron in 1943[8], which served as the foundation for Rosenblatt's development of the Perceptron model in 1957. The Perceptron model, however, assumed that information is digital in nature, which can be considered a drawback since unicellular organisms actually receive analog signals. Initially, these models were based on the functioning of multicellular organisms, and at the time, a simple logic gate model of the neuron seemed plausible. However, subsequent significant advancements in microbiology have revealed the limitations of these models, rendering them no longer credible.It has become evident through these advancements that information processing and harvesting capabilities are not exclusive to multicellular organisms but are also present in unicellular organisms. In fact, it is believed that during the evolutionary process, unicellular organisms aggregated to form multicellular organisms. For instance, the work of Jennings demonstrated complex decision-making abilities in a single-celled organism, Stentor, which is equipped with beating hairs known as cilia [3]. In his experiments, Jennings observed that when Stentor was subjected to an irritant, such as carmine powder directed at its mouth, it would first bend away, then reverse the beating of its cilia to expel the powder, contract, and finally detach. This behavior showcased Stentor's ability to confront a stimulus with one response and adapt to a more costly approach if the irritant persisted. Such observations challenge the notion that a network of neurons is necessary for rudimentary information processing [11] [4].

Biological processes like photosynthesis in unicellular organisms occur at the nanoscale. Fleming's experiment, published in Nature, illustrates that during photosynthesis, energy transfer within the FMO (Fenna–Matthews–Olson) complex is optimised by quantum phenomenon [5]. When viewed in this way, the system is essentially performing a single quantum computation, sensing many states simultaneously and selecting the correct answer, as indicated by the efficiency of the energy transfer[12]. Lyon [9] writes "while cognitive scientists for many years have tried to draw principled distinctions between 'metabolic' and 'cognitive' function (even in microbes ...), this dividing line is increasingly difficult to defend even in human beings" This suggests optimising metabolic activities lead to optimal decision making too. This highlights how information harvesting can lead to near-perfect decision-making. We believe that modeling these quantum phenomena into neurons could lead to the next step in the evolution of neural networks.

This project aims to construct a model based on how a single cell utilises its time-evolved intelligence to make decisions through quantum computation, employing the framework of pilot wave theory. Therefore, we focus on very simple organisms such as prokaryotes to find tractable examples of informationally guided energy harvesting [2]. We will pursue two approaches explained in the introduction section. This mathematical model could be extended to offer a novel perspective on Wayfinding Theory through the application of the Schrödinger Equation. As part of the project, we will develop open source codes for the tasks in Section 2.

Introduction

Recent research suggests that energy transfer in complex biological and chemical systems involves quantum coherence, even in ambient temperature conditions. Notably, this phenomenon has been observed in certain

photosynthetic proteins [12]. Understanding the light-initiated chain of events in photosynthetic solar energy conversion by plants, algae and bacteria has been the focus of extensive investigation over the past century. The efficiency of energy transfer has prompted considerable exploration of FMO proteins isolated from photosynthetic organisms to uncover underlying mechanisms. The intricate dynamics of quantum coherence, previously overlooked, play a significant role in energy transfer involving oscillatory populations of donors and acceptors. Fleming has provided direct evidence of remarkably long-lived electronic quantum coherence in the FMO complex [5] [2]. In this project, we model information processing in cells in two approaches.

The first approach, the statistical approach, proposes a model for a simple discrimination task using a quantum wave function, based on the double-slit experiment. In this experiment, a succession of individual particles create an interferece pattern on the photographic plate. This interference pattern contains information about the shape of the two slits. Consider a biological system where the organism's sensory system responds to an external object by encoding it through a process of transduction, generating an electrochemical signal that carries an analog representation of the external event along a signaling pathway (such as the optic nerve) into protected organelle(we call it Probium). Inside the Probium, this transduced signal forms an irregular analog shape. The task of the quantum wave function is to probe this irregular analog shape and create new information that is useful for the organism(for example whether the object is edible). The information harvesting task is to determine the appropriate category membership of this irregular analog shape to guide the organism on whether to ingest the object or not.

Inside the Probium, a particle is emitted to pass through some part of the irregular analog shape. The particle passes through the irregular analog shape, but the particle's associated quantum wave wraps around and through the particle in three dimensions, interfering with itself and creating a complex quantum wave form. This wave form now carries a quantum-transduced representation of the sensed object. The shape of this object has now been transported into the quantum domain, inside a walled organelle capable of maintaining quantum coherence for long enough to make it useful for the organism [6].

The emitted particle responds to this quantum wave form by generating new information. This information is active in the sense that it guides the subsequent movement of the particle along a specific Bohmian trajectory. The organism uses an ensemble of such trajectories, forming an interference pattern fingerprint, as a decision system to determine whether to ingest the external object or not. This entire process constitutes an act of information harvesting.

The second approach,which we refer to as the instantaneous approach, is based on the model proposed in Engel et al. (2007)[5]. This is an experimental evidence for wavelike energy transfer through quantum coherence in photosynthetic systems. They write,

"Superposition states formed during a fast excitation event allow the excitation to reversibly sample relaxation rates from all component exciton states, thereby efficiently directing the energy transfer to find the most effective sink for the excitation energy (which, in the isolated FMO complex, is the lowest energy state). When viewed in this way, the system is essentially performing a single quantum computation, sensing many states simultaneously and selecting the correct answer, as indicated by the efficiency of the energy transfer."

In this account, the excitation event (in effect, the particle) is given agency: the superposition states enable it to "reversibly sample" multiple possible trajectories and realize the optimal one every time. This presents a highly efficient paradigm for quantum computation; however, it makes claims that are incompatible with the widely accepted Copenhagen interpretation.

We model Fleming's experiment with Bohmian mechanics instead. The Bohm model is causal and includes an explicit model of information gathering by the quantum wave. The particle's trajectory is influenced by the quantum wave, more precisely, the pilot wave. As the edible or inedible item approaches the cell wall, the ionic distribution changes in the protein molecules. This change in ionic distribution is reflected in the electrostatic potential of the system. There are many such protein molecules placed at certain cardinal locations in the FMO complex. Nature has chosen these protein locations through an evolutionary process. Due to the presence of a multiple number of proteins in the FMO complex, the superposition of wave functions leads to quantum coherence. We will explicitly set different potentials to simulate the FMO complex and then pass the photon particle through. The path taken will determine the final decision of the system (edible or inedible?).

The paper [10] on mitochondrial signal transduction delves into the evolutionary history of mitochondria and underscores the close relationship between energy efficiency and survival, particularly emphasizing the importance of speed:

For organisms, achieving faster responses to changing bioenergetic conditions enables quicker transitions to new optimal states, maximizing energetic efficiency and minimizing the risk of damage. Thus, mitochondria play a crucial role in optimizing cellular and organismal behavior towards health, defined as optimal responsiveness to challenges, necessitating mechanisms that transmit information from organelle to organism [10].

This frames the adaptive problem that arguably favors instantaneous quantum computational processes. We witness this in Fleming's description of photosynthesis. Essentially, what needs to be developed is the concept that organisms evolve to represent potential energy expenditure in a spatial topology.

To illustrate with a high-level example: when considering the various paths to reach the grocery store, the idea is that these paths are analogically encoded in the probium in a manner reflecting the physical cost of each. An analog mind representing the relevant dimension of cost in a material structure inside the probium is needed. In this analog world, the quantum wave function can reliably select the path with the least action, allowing for the generalization of quantum wayfinding.

The outcome of this instantaneous computation must then be transmitted from the organelle to the cell's communication system, possibly through transduction into neurotransmitters. These neurotransmitters are packaged into synaptic vesicles and transported down the axon using specialized proteins like kinesin, which traverse the neuron's internal highway system, the microtubules. These vesicles accumulate at the axon terminal, awaiting release upon the arrival of an electrical signal. This enables the computational outputs of several mitochondria to be aggregated in vesicles and transmitted for further processing in daughter cells through spreading activation.

Each branch of this spreading activation must be evaluated dynamically. A simple model would involve invoking internal criteria for pre-conscious pruning, allowing only the winner to manifest in consciousness.

In the RedHen project for GSoC 2024, titled ***Quantum Wave Function for Information Processing***, our goal is to model how unicellular organisms categorize and make decisions when encountering various small objects such as food particles, dissolved molecules, fluids, or non-food items, all while operating within the constraints of limited cognitive resources.

The main task involves developing a computational model for processing analog information using Schrödinger's wave equation. This model utilizes the unique property of a quantum wave function, which contains multiple valid solutions, yet only one becomes observable. During this process, the wave function permeates the "probium," an entity we propose to exist within a cellular subsystem, potentially a mitochondrial organelle. This probium features a pair of openings reminiscent of those utilized in the double-slit experiment.

1 Background

1.1 Light Harvesting in Photosynthesis [5]

In photosynthesis, the reaction center holds six pigment molecules with the ability to absorb photons. Among these, the central pair, termed the special pair, is positioned closely together, fostering a robust electronic interaction between their excited states. This proximity facilitates the coherent sharing of excitation, giving rise to what is termed an exciton.

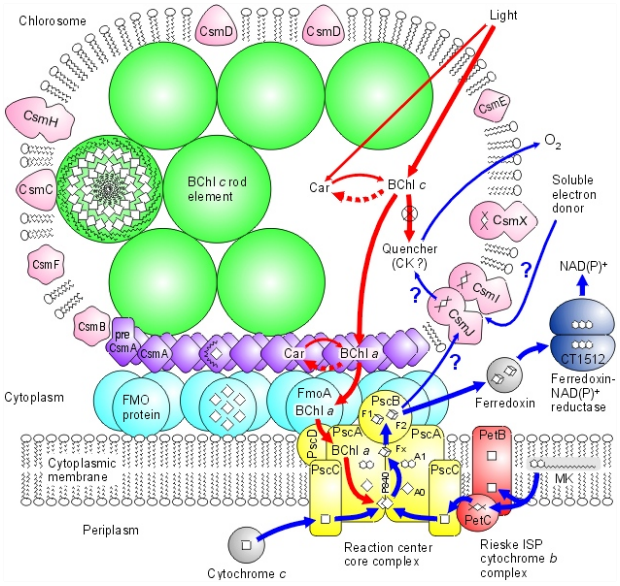


Figure 1: Photosynthesis and Light Harvesting

The components neighboring the reaction center, often called antenna proteins, are responsible for absorbing photons and transferring the resulting excitation energy to the special pair. Within these antenna proteins, pigment molecules exhibit distinct circular arrangements, resembling the relative orientation

observed in the special pair within the reaction center. The close grouping of pigments in the inner ring promotes the formation of exciton states, thereby improving the efficiency of capturing and transferring excitation energy compared to individual pigments.

The swift transmission of excitations across significant distances, spanning many tens of nanometers, serves to minimize energy loss to the surrounding environment, resulting in a light-harvesting efficiency exceeding 95%. Achieving such remarkable quantum efficiency necessitates relatively strong couplings to facilitate rapid transport to the reaction center, while also ensuring avoidance of coupling to trap states. A similar principle is observed in the nutritional processes of unicellular organisms.

Life on Earth originated from unicellular organisms millions of years ago. Within these organisms, all life processes, including digestion, excretion, and respiration, occur within a single cell. Various types of unicellular organisms exist, such as bacteria, protozoa, algae, fungi, and others. Within these organisms, organelles such as mitochondria orchestrate various activities without intelligent networks.

1.2 Mitocondrial Signal Transduction [10]

The concept of mitochondria solely as powerhouses is outdated. Mitochondria are living, dynamic organelles inherited maternally, responsible for transforming energy, synthesizing molecules, and transmitting signals within cells. Martin [10] has proposed that mitochondria act as the cell's processors, forming the Mitochondrial Information Processing System (MIPS) alongside the nucleus and other organelles. Mitochondrial signal transduction involves three primary processes:

- Sensing: Mitochondria possess the capability to perceive metabolic and hormonal signals, converting them into changes in mitochondrial structure, biochemistry, and function.
- Integration: This entails the amalgamation of various inputs into common responses, facilitated by communication between mitochondria and other organelles. The state of the mitochondrial network and the cell influences this integration.
- Signaling: Mitochondria generate outputs, or signals, that convey information locally to regulate metabolic pathways and influence other organelles, including nuclear gene expression. These signals also extend systemically to modulate physiology and organismal behavior.

By converting inputs into outputs, mitochondria can relay metabolic, biochemical, and neuroendocrine signals, aiding organismal adaptation. This perspective underscores the importance of mitochondrial communication and offers insights into their role in inter-organ processes crucial for human health.

2 Goals and Objectives

- ✓ Python Code: Time Dependent Schrodinger Equation in 3D (*vide* 2.1 – 2.6)
- ✓ Python Code: Wave function to Probability Density Function (*vide* 2.4)
- ✍ Mathematical Formulation of Quantum Wave Function to Decision-Making (*vide* 2.7)
- ✓ Python Code: Quantum Potential and Pilot Wave Trajectory
- ✍ Python Code: System Tuning to arrive a decision based on edible/ inedible object
- ✓ Python code: Time dependent formation of fringes for double slit, double annular slit, central hole
- ✍ Python Code : Anumation

2.1 Time-Dependent Schrodinger's Wave Equation

Schrodinger Equation is

$$i\hbar\frac{\partial}{\partial t}\psi(\mathbf{r},t) = -\frac{\hbar^2}{2m}\nabla^2\psi(\mathbf{r},t) + V(\mathbf{r},t)\psi(\mathbf{r},t) \tag{1}$$

2.2 Wave Function ψ

The wave function provides complete description of all properties of matter at the atomic and molecular lavel. Wave Function is a function of position and time. Time dependent $\psi(\mathbf{r},t)$ carries dynamical observables (experimentally measured/ observed viz., position, momentum, energy, etc.) but it is not directly observable in the experiment. Experimental observables depend on $\psi\psi^* = |\psi|^2$. If ψ is normalized then Probability Density $\int_{-\infty}^{+\infty}|\psi|^2dx = 1$

2.3 Check: ψ acceptable?

- ✓ $\psi\psi^*$ must be single valued.
- ✓ Value of ψ should not blow-up for all x, y, z, t
- ✓ First derivative of ψ finite and continuous
- ✓ Normalizable, Solution ψ if not-normalizable, is not a wave function, No statistical interpretation can be drawn.
- ✓ ψ Continuous everywhere
- ✓ Probability Density $\int_{-\infty}^{+\infty} |\psi|^2 dx = 1$

2.4 $\psi\psi^*$ Probability Density and Normalizing

How can a delocalized mathematical function (wave function) represent a particle which is supposed to be localized (according to classical concept)? $\int_x^{x+\delta x} \psi^*\psi dx$ is the probability of finding the particle in space x to $x + \delta x$. Total Probability density = 1. So, Normalized Wave function as acceptable solution of the Time Dependent Schrodinger Equation (TDSE). How to Normalize:

$$\psi \equiv \frac{\psi}{\sqrt{\int_V \psi\psi^* dV}}$$

In our case, we assume Gaussian wave front. Initially if we normalize at $t = 0$ then ψ is also normalized for all time = t. TDSE automatically normalized .

Assume gaussian wave function: $\psi(x,0)Ae^{-ax^2}$ the Normalized Gaussian Wave Function at $t = 0$ $\psi(x,0) = \left(\frac{2a}{\pi}\right)^{\frac{1}{4}} e^{-ax^2}$

Time Evolution of Normalizing Factor is zero:

$$\int_{-\infty}^{+\infty} \frac{\partial}{\partial t}|\psi(x,t|^2 dx = \frac{i\hbar}{2m}\left[\psi^*\frac{\partial\psi}{\partial x} - \frac{\psi^*}{\partial x}\psi\right]_{-\infty}^{+\infty} = 0$$

because $\psi = \psi^* = 0$ at $x = \pm\infty$ hence, we can say the normalizing factor is time independent.

Normalize the wavefunction of a Gaussian wave packet, centered on $x = x_0$ with characteristic width σ :

$\psi(x) = \psi_0 e^{-\frac{(x-x_0)^2}{4\sigma^2}} dx$

Solution

To determine the normalization constant ψ_0

$|\psi_0|^2 \int_{-\infty}^{+\infty} e^{-\frac{(x-x_0)^2}{4\sigma^2}} dx = 1$

Changing the variable of integration to $y = \frac{(x-x_0)}{\sqrt{2}\sigma}$, we get

$|\psi_0|^2\sqrt{2}\sigma \int_{-\infty}^{+\infty} e^{-y^2} dy = 1$

However, from an integral table we know $\int_{-\infty}^{+\infty} e^{-y^2} dy = \sqrt{\pi}$

which implies that $|\psi_0|^2 = \frac{1}{\sqrt{2\pi\sigma^2}}$

Hence, a general normalized Gaussian wavefunction takes the form $\psi(x) = \frac{e^{i\phi}}{(2\pi\sigma^2)^{0.25}} e^{-\frac{(x-x_0)^2}{4\sigma^2}}$ where ϕ is an arbitrary real phase-angle.

2.5 3D-TDSE Solution Crank-Nicholson Method

Assuming $m = 1$, $\hbar = 1$

$$\frac{\partial\psi(x,y,z,t)}{\partial t} = \frac{\psi_{i,j,k}^{n+1} - \psi_{i,j,k}^{n}}{\Delta t}$$

$$\frac{\partial^2\psi(x,y,z,t)}{\partial x^2} = \frac{1}{2(\Delta x)^2}\left[\left(\psi_{i+1,j,k}^{n+1} - 2\psi_{i,j,k}^{n+1} + \psi_{i-1,j,k}^{n+1}\right) + \left(\psi_{i+1,j,k}^{n} - 2\psi_{i,j,k}^{n} + \psi_{i-1,j,k}^{n}\right)\right]$$

$$\frac{\partial^2\psi(x,y,z,t)}{\partial y^2} = \frac{1}{2(\Delta y)^2}\left[\left(\psi_{i,j+1,k}^{n+1} - 2\psi_{i,j,k}^{n+1} + \psi_{i,j-1,k}^{n+1}\right) + \left(\psi_{i,j+1,k}^{n} - 2\psi_{i,j,k}^{n} + \psi_{i,j-1,k}^{n}\right)\right]$$

$$\frac{\partial^2\psi(x,y,z,t)}{\partial z^2} = \frac{1}{2(\Delta z)^2}\left[\left(\psi^{n+1}_{i,j,k+1} - 2\psi^{n+1}_{i,j,k} + \psi^{n+1}_{i,j,k-1}\right) + \left(\psi^{n}_{i,j,k+1} - 2\psi^{n}_{i,j,k} + \psi^{n}_{i,j,k-1}\right)\right]$$

$$V(x,y,z,t)\psi(x,y,z) = \frac{1}{2}\left[V^{n+1}_{i,j,k}\psi^{n+1}_{i,j,k} + V^{n}_{i,j,k}\psi^{n}_{i,j,k}\right]$$

$$r_x = -\frac{\Delta t}{2i(\Delta x)^2}$$

$$r_y = -\frac{\Delta t}{2i(\Delta y)^2}$$

$$r_z = -\frac{\Delta t}{2i(\Delta z)^2}$$

Assume $m = 1$, $\hbar = 1$ and

$$\begin{aligned}\psi^{n+1}_{i,j,k} - \psi^{n}_{i,j,k} = {} & r_x\left[\left(\psi^{n+1}_{i+1,j,k} - 2\psi^{n+1}_{i,j,k} + \psi^{n+1}_{i-1,j,k}\right) + \left(\psi^{n}_{i+1,j,k} - 2\psi^{n}_{i,j,k} + \psi^{n}_{i-1,j,k}\right)\right] + \\ & r_y\left[\left(\psi^{n+1}_{i,j+1,k} - 2\psi^{n+1}_{i,j,k} + \psi^{n+1}_{i,j-1,k}\right) + \left(\psi^{n}_{i,j+1,k} - 2\psi^{n}_{i,j,k} + \psi^{n}_{i,j-1,k}\right)\right] + \\ & r_z\left[\left(\psi^{n+1}_{i,j,k+1} - 2\psi^{n+1}_{i,j,k} + \psi^{n+1}_{i,j,k-1}\right) + \left(\psi^{n}_{i,j,k+1} - 2\psi^{n}_{i,j,k} + \psi^{n}_{i,j,k-1}\right)\right] + \\ & \frac{\Delta t}{2i}\left[V^{n+1}_{i,j,k}\psi^{n+1}_{i,j,k} + V^{n}_{i,j,k}\psi^{n}_{i,j,k}\right]\end{aligned}$$

$$\begin{aligned}&-r_x\psi^{n+1}_{i+1,j,k} - r_y\psi^{n+1}_{i,j+1,k} - r_z\psi^{n+1}_{i,j,k+1} + a_{i,j,k}\psi^{n+1}_{i,j,k} - r_x\psi^{n+1}_{i-1,j,k} - r_y\psi^{n+1}_{i,j-1,k} - r_z\psi^{n+1}_{i,j,k-1} = \\ &r_x\psi^{n+1}_{i+1,j,k} + r_y\psi^{n+1}_{i,j+1,k} + r_z\psi^{n+1}_{i,j,k+1} + b_{i,j,k}\psi^{n+1}_{i,j,k} + r_x\psi^{n+1}_{i-1,j,k} + r_y\psi^{n+1}_{i,j-1,k} + r_z\psi^{n+1}_{i,j,k-1}\end{aligned}$$

where

$$a_{i,j,k} = (1 + 2r_x + 2r_y + 2r_z + \frac{i\Delta t}{2}V^{n+1}_{i,j,k})$$

and

$$b_{i,j,k} = (1 - 2r_x - 2r_y - 2r_z - \frac{i\Delta t}{2}V^{n}_{i,j,k})$$

Formula:

$$A[i,j,k] = n^2 * i + n * j + k + 1$$

2.6 One Particle Wave Function Trajectory

The Schrodinger Equation for a system of N particles interacting through a potential V is given by whare m_i is the mass of the particle i and ∇_i^2 the Laplacian operator with respect to that particle's coordinates. The vector $\mathbf{r}$ now stands for the position in configuration space.

$$i\hbar\frac{\partial}{\partial t}\psi(\mathbf{r},t) = -\sum_{i=1}^{N}\frac{\hbar^2}{2m_i}\nabla_i^2\psi(\mathbf{r},t) + V(\mathbf{r_1},\mathbf{r_2},..,\mathbf{r_N},t)\psi(\mathbf{r},t) \tag{2}$$

In the first step, we will focus here the interference of one particle then there will be only one mass.

$$i\hbar\frac{\partial}{\partial t}\psi(\mathbf{r},t) = -\frac{\hbar^2}{2m}\nabla^2\psi(\mathbf{r},t) + V(\mathbf{r},t)\psi(\mathbf{r},t)$$

To get the hydrodynamic equations, we substitute $\psi(\mathbf{r},t) = \sqrt{P(\mathbf{r},t)}e^{iS(\mathbf{r}.t)}$ in the above equation. Where P and S are real dimentionless functions and P is non-negative.

Equating separately the real and imaginary parts, we obtain

$$\frac{\partial P}{\partial t} = -\frac{\hbar}{m}\nabla.(P\nabla S) \tag{3}$$

Quantum Hamiltonian Jacobi Equation

$$\frac{\partial S}{\partial t} = -\frac{\hbar}{2m}(\nabla S)^2 - Q - V(\mathbf{r},t) \tag{4}$$

Here, Q, the quantum potential, $Q = -\frac{\nabla^2\sqrt{P}}{2\sqrt{P}}$ hence the Hamiltonian of the Schrodinger Equation becomes Quantum Hamiltonian-Jacobi.

The Bohmian trajectories of the particle are defined by $\mathbf{v} = \nabla S$ and we rewrite the above two equations as follows:

$$\frac{DP}{Dt} = -\frac{\hbar}{m}P\nabla.\mathbf{v}$$

$$\frac{D\mathbf{v}}{Dt} = -\frac{\hbar}{2m}\nabla(Q+V)$$

where Lagrangian derivative is defined as $\frac{DP}{Dt} = \nabla$

Above two equations, together with

$$\frac{D\mathbf{r}}{Dt} = \mathbf{v}$$

must be solved to get the Bohmian trajectories and, eventually the wave function.

One should note: Using Particular Integral (PI) we get solution of continuity equation $\left(\frac{\partial}{\partial t} + \mathbf{v}.\nabla\right)\rho = 0$ is $\rho(\mathbf{r}, t+dt) = e^{-(\nabla.\mathrm{v})dt}\rho(\mathrm{r}.t)$

2.7 Numerical Solution

Continuity Equation

$$\frac{DP}{Dt} = -\frac{\hbar}{m}P\nabla.\mathbf{v}$$

$$\frac{\partial P}{\partial t} + \mathbf{v}\nabla P = -\frac{\hbar}{m}P\nabla.\mathbf{v}$$

Put $P = e^{2g(t)}$ and $\nabla g = 0$ then

$$2e^{2g}\frac{\partial g}{\partial t} + 2\mathbf{v}e^{2g}\nabla g = -e^{2g}\nabla.\mathbf{v}$$

$$\frac{\partial g}{\partial t} = -\frac{1}{2}\nabla.\mathbf{v}$$

$$g_n(t+\Delta t) = g_n(t) - \frac{\hbar}{2m}\Delta t\nabla.\mathbf{v}$$

Quantum Hamiltonian Jacobi Equation

$$\frac{D\mathbf{v}}{Dt} = -\frac{\hbar}{2m}\nabla(Q+V)$$

$$\frac{\partial v}{\partial t} + \mathbf{v}.\nabla\mathbf{v} = -\frac{\hbar}{2m}\nabla(Q+V)$$

$$\frac{\partial v}{\partial t} = -\frac{\hbar}{2m}\nabla(Q+V)$$

$$\mathbf{v}_n(t+\Delta t) = \mathbf{v}_n(t) - \frac{\hbar}{2m}\Delta t\nabla(Q+V)$$

Trajectory

$$\frac{D\mathbf{r}}{Dt} = \mathbf{v}$$

$$\frac{\partial \mathbf{r}}{\partial t} + \mathbf{v}.\nabla\mathbf{r} = \mathbf{v}$$

$$\mathbf{r}_n(t+\Delta t) = \mathbf{r}_n(t) + \Delta t\mathbf{v}_n(t) \tag{5}$$

Quamtum Potential, Q

$$Q = -\frac{\nabla^2\sqrt{P}}{2\sqrt{P}} = -\frac{\nabla\cdot\nabla\sqrt{P}}{2\sqrt{P}} = -\frac{\nabla\cdot\nabla e^g}{2e^g} = -\frac{\nabla\cdot(e^g\nabla g)}{2e^g}$$

since, $\nabla(\phi\mathbf{F}) = \nabla\phi \cdot \mathbf{F} + \phi\nabla \cdot \mathbf{F}$ here $\phi = e^g$ and $F = \nabla g$ hence,

$$Q = -\frac{\nabla e^g \cdot \nabla g + e^g \nabla \cdot \nabla g}{2e^g} = -\frac{e^g(\nabla g)^2 + e^g \nabla^2 g}{2e^g} = -\frac{\hbar}{2m}(\nabla g)^2 + \nabla^2 g) \tag{6}$$

Non-Gauge Field Trajectory

$$\frac{d\mathbf{r}(t)}{dt} = \frac{\hbar}{m} Im\left[\frac{1}{\psi}\nabla\psi\right]$$

$$\mathbf{r}_n(t + \Delta t) = \mathbf{r_n}(\mathbf{t}) + \Delta t \frac{\hbar}{m} Im\left[\frac{1}{\psi}\nabla\psi\right] \tag{7}$$

2.8 3D Gaussian Wavefront

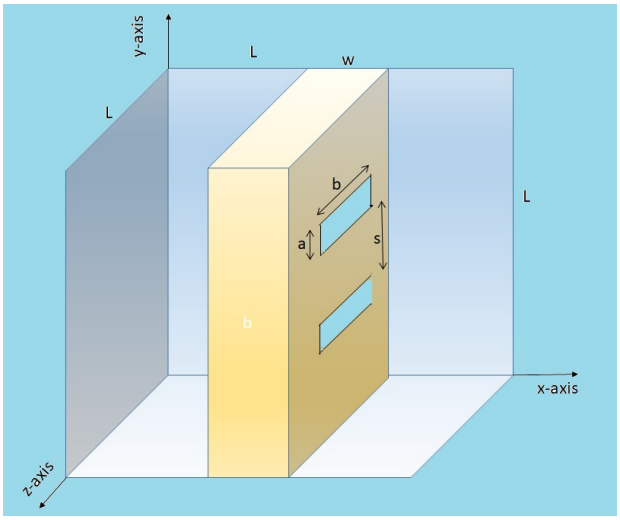


Figure 2: Double Slit in 3D

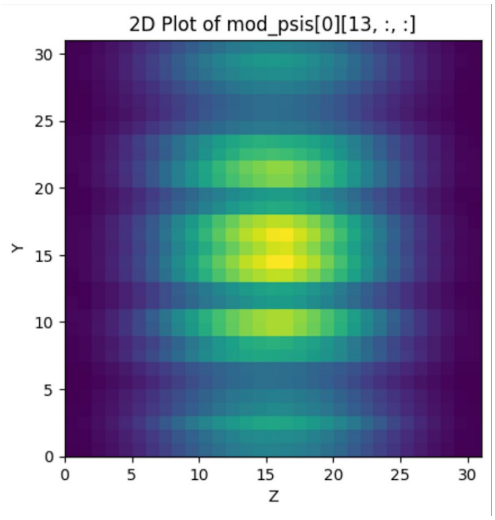


Figure 3: Two Dimentional Fringes, Gaussian intensity distribution on YZ-plane

The corresponding elliptical Gaussian function corresponding to $\sigma_y \neq \sigma_z$ is given by [13]

$$\psi(x_i, y_i, z_i, t = 0) = \frac{1}{2\pi\sigma_y\sigma_z} e^{-\left[\frac{(x-\mu_y)^2}{2\sigma_y^2} + \frac{(x-\mu_z)^2}{2\sigma_z^2}\right]} \tag{8}$$

2.9 Bohmian Trajectory with Classical and Quantum Potential

Let $\psi(\mathbf{r}, t) = \sqrt{P(\mathbf{r}, t)} e^{\frac{i}{\hbar}S(\mathbf{r}.t)}$ rewrite in one-dimension $\psi(x, t) = A(x, t)e^{\frac{i}{\hbar}S(x,t)}$

$$i\hbar\left[\frac{\partial A}{\partial t}e^{\frac{i}{\hbar}S(x,t)}+A\frac{i}{\hbar}\frac{\partial S}{\partial t}e^{\frac{i}{\hbar}S}\right]=\frac{\hbar^2}{2m}\left[\frac{\partial^2 A}{\partial x^2}+2\frac{\partial A}{\partial x}\frac{i}{\hbar}\frac{\partial S}{\partial x}+A\frac{\partial^2 S}{\partial x^2}-\frac{A}{\hbar^2}\left(\frac{\partial S}{\partial x}\right)^2\right]e^{\frac{i}{\hbar}S}+VAe^{\frac{i}{\hbar}S}$$

Taking real part we get,

$$-A\frac{\partial S}{\partial t}=\frac{\hbar^2}{2m}\frac{\partial^2 A}{\partial x^2}+\frac{A}{2m}\left(\frac{\partial S}{\partial x}\right)^2+VA$$

or,

$$\frac{\partial S}{\partial t}+\frac{1}{2m}\left(\frac{\partial S}{\partial x}\right)^2+V=\frac{\hbar^2}{2mA}\frac{\partial^2 A}{\partial x^2}$$

where $Q=\frac{\hbar^2}{2mA}\frac{\partial^2 A}{\partial x^2}$
or,

$$\frac{\partial S}{\partial t}+\frac{1}{2m}\left(\frac{\partial S}{\partial x}\right)^2=-(V+Q)$$

or,

$$\frac{\partial}{\partial x}\left[\frac{\partial S}{\partial t}+\frac{1}{2m}\left(\frac{\partial S}{\partial x}\right)^2\right]=-\frac{\partial}{\partial x}(V+Q)$$

or,

$$\frac{\partial^2 S}{\partial x\partial t}+\frac{1}{2m}2\frac{\partial S}{\partial x}\frac{\partial^2 S}{\partial x^2}=-\frac{\partial}{\partial x}(V+Q)$$

Since, $m\mathbf{v}=\frac{\partial S}{\partial x}$ we get $\frac{\partial^2 S}{\partial x^2}=m\frac{\partial v}{\partial x}$ also we know that $\frac{\partial^2 S}{\partial x\partial t}=\frac{\partial^2 S}{\partial t\partial x}$
We rewrite above equation as below:

$$\frac{\partial^2 S}{\partial t\partial x}+\frac{1}{2m}2\frac{\partial S}{\partial x}\frac{\partial^2 S}{\partial x^2}=-\frac{\partial}{\partial x}(V+Q)$$

$$m\frac{\partial v}{\partial t}+mv\frac{\partial v}{\partial x}=-\frac{\partial}{\partial x}(V+Q)$$

We know that $v=v(x,t)$ therefore, $\mathrm{dV}=\frac{\partial v}{\partial t}dt+\frac{\partial v}{\partial x}dx=\frac{\partial v}{\partial t}dt+\frac{\partial v}{\partial x}v=\left[\frac{\partial v}{\partial t}+\frac{\partial v}{\partial x}v\right]dt$ Thus above equation reduces to (in one-dimension)

$$m\frac{dv}{dt}=-\frac{\partial}{\partial x}(V+Q)$$

And in three-dimension

$$m\frac{dv}{dt}=-\nabla(V+Q)$$

Thus we get net force on the particle is a sum of classical force $-\nabla V$ and quantum force $-\nabla Q$ and local velocity

$$\mathbf{v}=\frac{1}{m}\nabla S \tag{9}$$

2.10 Self-supervised Learning

The chromophores within the FMO complex should be positioned and oriented among themselves in a way that allows them to learn automatically. A schematic of self supervised learning is given below.

3 Project Implementation [1]

3.1 Python Coding

The primary emphasis of this project is on the development of Python code. In Section 2, all essential mathematical expressions and formulas are elucidated. We have to write codes for individual modules and subsequently integrate them to form the simulation code for the model. As mentioned in the introduction section, we have outlined two approaches for decision-making through quantum information processing. Therefore, we will proceed to implement these two approaches one after the other. The software modules to be implemented are listed below.

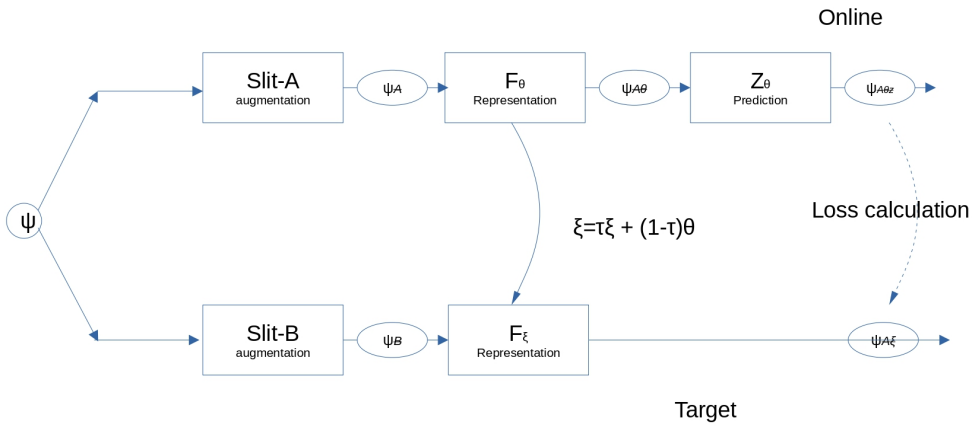


Figure 4: BYOL Architecture

- Photon Generator (Source)
- Gaussian Wave Function Initialization
- Solve Time Dependent Schrodinger Equation
- Double-Slit Interaction
- Bohm Trajectory
- Solving Quantum Jacobi Hamiltonian
- Animation

Initially, all modules are to be written for one dimension, and we must test the codes against expected results. Subsequently, we will extend the codes to three dimensions; a brief implementation is outlined in sub-section 3.2. Then we will extend it for multibody system. Each step of the implementation is detailed in Section 4.

3.2 Implementation

HPC Hardware: We will be using T4 GPU (2560 cores) which is operating at a frequency of 585 MHz, which can be boosted up to 1590 MHz, memory is running at 1250 MHz (10 Gbps effective). Total GPU RAM 6GB.

Software Libraries: For solving 3D Schrodinger Equation and Bohmian Trajectories we will use Crank Nicolson method. We will store the linear equations in sparse matrix as most of the terms are zeroes. Therefore, specific Python Libraries will be used. CuPy provides sparse matrix which support complex numbers. CuPy also provides *spsolve* function which is used to solve linear equations (even with complex numbers) as long as the sparse matrix are in compressed sparse row (CSR) or compressed sparse column (CSC) format. CuPy provides GPU support.

Software development and implementaion is discussed below.

Statistical Approach

- Double-slit: Large number of randomly oriented particles are passed through double-slit opening. These particles are non-interacting and emitting one by one from the source. According to Pilot Wave Theory, the wave function guides the particle (9). Therefore, we have to solve Time Dependent Schrodinger Equation (1) to get the wave function using Crank Nicolson Method (refer Section 2.5).
- Gaussian wave front: The intial wavefront for the Time-Dependent Schrödinger Equation is a Gaussian wavefront (8). This choice is beneficial as it facilitates the normalization of the wave function.

Secondly, gaussian wavefront can be tested in every time-steps. This can be used a test case for code verification.

- Solving the Quantum Jacobi Hamiltonian: We need to implement the moving weighted least squares (MWLS) algorithm to compute derivatives of a function defined on an unstructured grid. Equation (4) is called Quantum Jacobi Hamitonian. The velocity of the partcle is obtained by (9) and Bohmian trajectory of the particle is obtained by (5).

- Replace the rectangular shape of the double-slit with a concentric annular cut. This will result in circular fringes appearing, making classification easier by locating the central maxima on the 2D screen.

- Using CuPy we have to implement large number of particles simulation using GPU to get the decision-making model using information harvesting.

The modules implemented in statistical approach will be extended to nutrition mechanism of unicellular organism. This we call instantenous approach because it leads to decision by only one photon. Here the system has got multiple slits with inbuilt intelligence and those slits are located at vairious precalculated sites. Quantum entanglement among the slits results in a decision with high accuracy.

Instantaneous Approach

- The experiment conducted by Fleming [5] will be modeled here, but the model will focus on the decision-making process of unicellular nutrition rather than photosynthesis. Fleming in 2007 claims photosynthesis is purely quantum phenomenon. But later it has been found that because of the size of protein complexes and the involvement of electronic degrees of freedom, computationally these systems need to be treated with a combined quantum–classical description [7]. As per equation (4) we find classical potential V and quantum potential Q. Therefore, it is a two step process. When edible/ inedible object adheres to the cell wall V developes in the space. This is equivalent to having 7 annular slits of similar shapes gets oriented in space.

- Quantum entanglement in the FMO complex is the key concept that energy transfer to the reaction center [5]. Here entanglement means it is a non-classical correlation between the electronic states of separated chromophores (electronic degrees of freedom). It is a multi-partite (it contains 7 chromophores) mixed-state (interaction with the environment) system. The entanglement is quite complicated, hence we simplify it as a single excitation subspace.

  Assumption: a) Model is excited by a single excitation (single photon enters at a time in the system). b) Non-perturbative and non-Markovian (Environment is almost constant with time)

- In the second step, a photon passes through slit-1 or slit-6, the system exhibits quantum coherence. Then enters slit-4,5,7 and comes out from slit-3. Because of quantum entanglements among multiple slits, superposition wave function occurs. Now ψ becomes a guiding wave and leads to decision classification by Bohmian trajectory equation (5).

- The information in unicellular organism is analog signal. Here, protein molecules changes orientation as per the analog signal it receives, thus analog signal is being encoded in the protein molecules. We model this structural orientation of 7 protein molecules as spatially distributed annular slits.

- Positioning of these protein molecules in FMO complex is a evolutionary process in nature. Therefore, we need a trained system of slits with entanglement cofficients. There is no labeled dataset available but we have to train the whole model. We will simulate this evolution as a self-supervised learning process.

- This self-supervised learning is the heart of this unicellular nutrition model. This learning determines the distribution of classical potential V in the space. Once the self-supevised model is ready, we have to get the ψ as a superposition of 7 slits. This coherent wave function is the pilot wave that leads the photon to the decision system (like mitocondria). Which is a binary classifier based on position of light spot on the photographic plate (mitocondria).

3.3 Challanges

We have two approaches to quantum information processing. The first approach is straight forward whereas the second approach is a two step process which needs self supervised learning to determine:-

- Orientation of Chromophores in FMO due to the classical potential V.
- Locating the proteins.

3.4 Summary

In this analog world, the quantum wave function can reliably select the path with the least action, allowing for the generalization of quantum wayfinding. The statistical approach, introduces a model for a straightforward discrimination task employing a quantum wave function, inspired by the double-slit experiment. In this experiment, a series of individual particles generate an interference pattern on the photographic plate, which encapsulates information regarding the configuration of the two slits. The instantaneous approach, the experiment conducted by Fleming, introduces a model where a single photon enters the system and makes a decision. Fleming in 2007 claims photosynthesis is purely quantum phenomenon. But later it has been found that because of the size of protein complexes and the involvement of electronic degrees of freedom, computationally these systems need to be treated with a combined quantum–classical description.

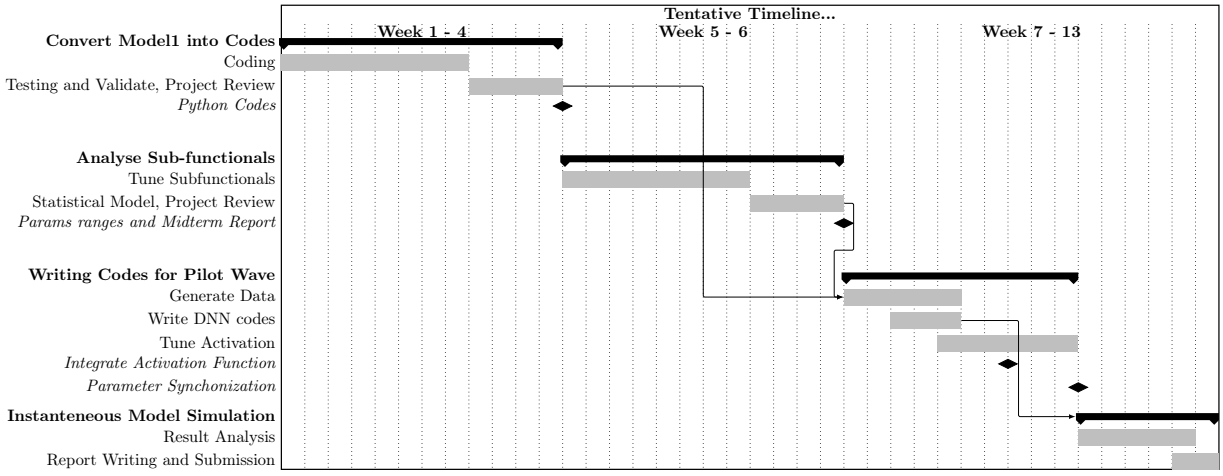
This work introduces a potentially groundbreaking concept of intelligence within the AI realm. It suggests that current AI models, relying on outdated neuron model, could be revolutionized. The study delves into simulations illustrating how nano-scale cellular organelles can leverage quantum physics for gathering information and making decisions. By examining cellular decision-making processes, this research lays the groundwork for a new era of AI development. Furthermore, this project has the potential to extend into Wayfinding Theory, enhancing decision-making accuracy post-information gathering.

4 Tentative Timeline

4.1 May 1 – May 26 : Community Bonding

- Enhance my understanding of Quantum Mechanics and Pilot Wave Theory
- Get to know my mentor and Redhen members
- Participate in community meetings and discussions to get familiar with the project's ecosystem
- Project Planning and Objectives
- Identify Potential Challenges and discuss possible solutions with Redhen team
- Review the existing codes, understand the testing and validation process needed
- Discuss stretch goals

The timeline provided below is tentative. Estimating the time accurately proves challenging due to the extensive testing of codes with boundary conditions required.



4.2 May 27 – Aug 19 : Timeline in Detail

- May 27 – June 2: Develop Python Code to solve Time-Dependent Schrodinger's Equation using Crank-Nicolson Method (vide section 2.1 – 2.9). Ensure proper Boundary Conditions. Initially write a monolithic code to assure the code functionality. CuPy library will be used in Crank-Nicolson method. Probablity density is easily calculated from the solution of Schrodinger's equation.
- June 3 – June 9: Code to calculate Quantum Potential from the estimated wave function assuming no gauge field interaction among the particles. Thus we will get the velocity of the particle under the guidance of pilot wave (5). Finally, derive the particle trajectory for non-gauge field in 3-dimension.
- June 10 – June 16: Testing and Validation as per Wave Function acceptability (vide. Section 2.2, 2.3). Test cases are listed in Section 2.3. Analyze the sub-functionals and generate the parameters after tuning the expected output.
- June 17 – June 23: Now we will consider gauge field interactions and use MWLS method(equation (7)). Write the code for MWLS method.
- June 24 – June 30: Testing and Validation as per Wave Function acceptability (vide. Section 2.2, 2.3). Test cases are listed in Section 2.3. All sub functional modules are ready. Analyze the sub-functionals and generate the parameters after tuning the expected output.
- July 1 – July 7: Change rectangular slit-shape to annular shape and vary the classical potential wells as per σ and μ. Code writing for multiple slits (seven slits) system. Parallelize the code for improved performance using CuPy Library.
- July 8 – July 12: **Midterm Evaluation.** Finalizing Model of first approach and submit a report to Red Hen Lab mentor.
- July 13 – July 21: We will model the FMO complex and adapt it for unicellular ingestion. FMO complex has got 7 chromophores forming a specific structure. We consider the 7 chromophores as 7 circular slits. The dimensions of the slits(σ and μ)(vide Section 2.8) will also be tunable. We will write code such that the 7 circular slits can be placed dynamically at 7 locations. We will also introduce quantum entanglement in the 7 slit system. If the two slits have common axes then quantum entanglement will be maximum and if the axes of the slits perpendicular to each other, then quantum entanglement is minimum. We will write the code such that orientation of the 7 slits can be dynamically changed.
- July 22 – July 28: We will develop a neural network to determine the parameters for the FMO model, including the position and orientation of slits, as well as the σ and μ values associated with the slits. The input for the neural network will be an analog signal represented as a time series, which will be based on the characteristics of the object, such as whether it is edible or inedible.
- July 29 – Aug 4: Test case generation and code validation.
- Aug 5 – Aug 11 : Model tuning and writing animation codes.
- Aug 12 – Aug 18 : Results and Analysis
- Aug 19 – 26 : Final Week GSoC for submission of my work product and my final mentor evaluation.

5 Possible Python usage

```
def normalize_psi(psi, x):
int_psi = scipy.integrate.simps(psi,x)
return psi/int_psi
```

```
scipy.integrate.tplquad(func, a, b, gfun, hfun, qfun, rfun, args=(), epsabs=1.49e-08, epsrel=1.49e-08
import numpy as np
from scipy import integrate
f = lambda z, y, x: x*y*z
integrate.tplquad(f, 1, 2, 2, 3, 0, 1)
(1.8749999999999998, 3.3246447942574074e-14)
```

————————3D volume integral ————————
A nice way to go about this would be using scipy's **tplquad** integration. However, to use that, we need a function and not a cloud point.

An easy way around that is to use an interpolator, to get a function approximating our cloud point - we can for example use scipy's RegularGridInterpolator if the data is on a regular grid:

```
import numpy as np
from scipy import integrate
from scipy.interpolate import RegularGridInterpolator

# Make data.
def function(x,y,z):
return x*y*z

N = 5
xmin, xmax = 0, 1
ymin, ymax = 0, 1
zmin, zmax = 0, 1
x = np.linspace(xmin, xmax, N)
y = np.linspace(ymin, ymax, N)
z = np.linspace(zmin, zmax, N)

values = function(*np.meshgrid(x,y,z, indexing='ij'))

# Interpolate:
function_interpolated = RegularGridInterpolator((x, y, z), values)

# tplquad integrates func(z,y,x)
f = lambda z,y,x : my_interpolating_function([z,y,x])

result, error = integrate.tplquad(f, xmin, xmax, lambda _: ymin, lambda _:ymax,lambda *_: zmin, lambd
```

Following code is Normalization of WeveFunction,....

```
import numpy as np
from scipy import integrate
from scipy.interpolate import RegularGridInterpolator

L=8
x0=L/2
y0=L/5

def psi0(x, y, x0, y0, sigma=0.5, k=15*np.pi):

"""
Proposed wave function for the initial time t=0.
Using NumPy arrays for calculations.
"""
return x*y
#return np.exp(-1/2*((x-x0)**2 + (y-y0)**2)/sigma**2)*np.exp(1j*k*(y-y0))#np.exp(-1/2*((y-y0)**2 + (z


# Make data.
def function(x,y,z):
return x*y*z

N = 5
xmin, xmax = 0, 1
ymin, ymax = 0, 1
zmin, zmax = 0, 1
x = np.linspace(xmin, xmax, N)
y = np.linspace(ymin, ymax, N)
```

```
z = np.linspace(zmin, zmax, N)

values = function(*np.meshgrid(x,y,z, indexing='ij'))

# Interpolate:
function_interpolated = RegularGridInterpolator((x, y, z), values)

# tplquad integrates func(z,y,x)
f = lambda z,y,x : function_interpolated([z,y,x])

result, error = integrate.tplquad(f, xmin, xmax, lambda _: ymin, lambda _:ymax,lambda *_: zmin, lambd
print(result)
############################################################
values = psi0(*np.meshgrid(x,y, indexing='ij'),x0,y0)

# Interpolate:
function_interpolated = RegularGridInterpolator((x, y), values)

# tplquad integrates func(z,y,x)
f = lambda y,x : function_interpolated([y,x])

result, error = integrate.dblquad(f, xmin, xmax, lambda _: ymin, lambda _:ymax)
print(result)
```

6 Some Results

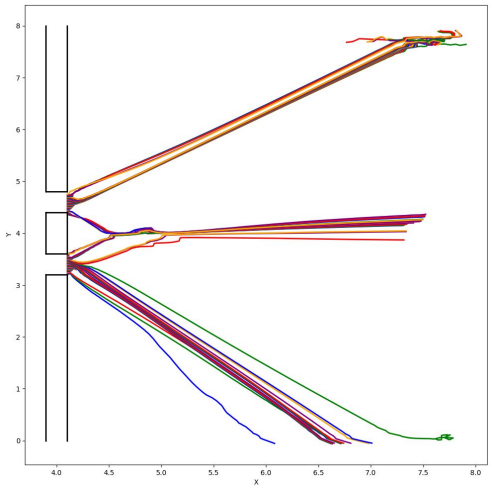


Figure 5: Bohmian Trajectories Double Slit Experiment

Central Hole

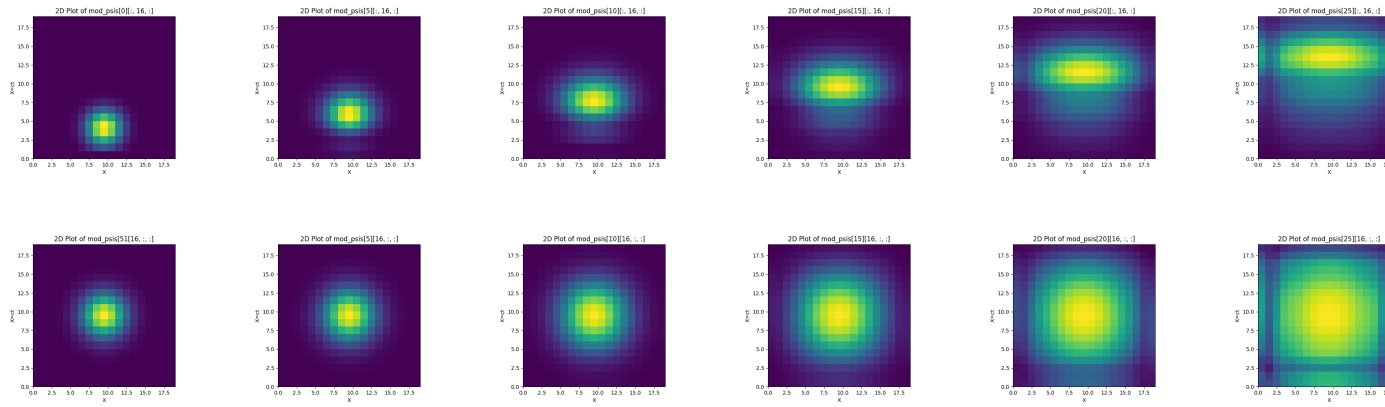


Figure 6: There is no slit, Gaussian 3D Wavefront. Top row shows wave front is advancing and the probalility is spreading gradually. Bottom row shows no fringe pattern evovled with time.

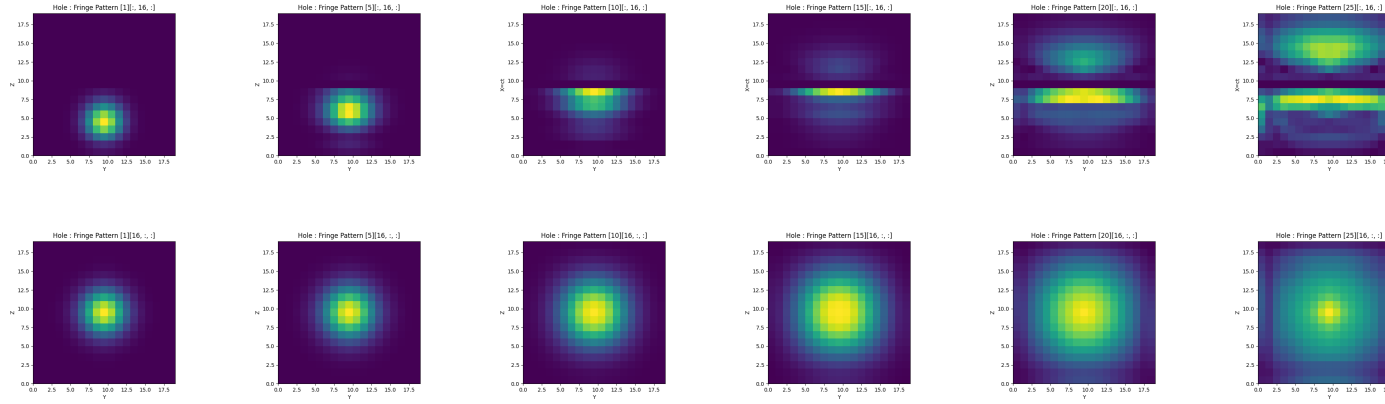


Figure 7: Central Hole Gaussian 3D Wavefront. Top row shows wave front is advancing and the probalility is spreading gradually. Bottom row shows evolution of fringe pattern with time.

7 Current status

Following codes are ready and available for the mentors 3 −

- ✓ Python Code: Solution of Time Independent Schrodinger Equation in 3D. Code Link.
- ✓ Python Code: Solution of Time Dependent Schrodinger Equation in 3D. Code Link.
- ✓ Python Code: Wave function to Probability Density Function. Code Link.
- ✍ Mathematical Formulation of Quantum Wave Function to Decision-Making
- ✓ Python Code: Quantum Potential and Pilot Wave Trajectory. Code Link
- ✍ Python Code: System Tuning to arrive a decision based on edible or inedible object
- ✓ Python code: Time dependent formation of fringes for double slit, double annular slit, central hole.Code Link
- ✍ Python Code : Animation

8 My Notes

8.1 Causal Interpretation

Polar form WaveFunction $\psi = R^{iS/\hbar}$. The particle is always accompanied by its ψ that the combined system of particle plus field is causally determined (the statistics merely apply to an ensemble of causally

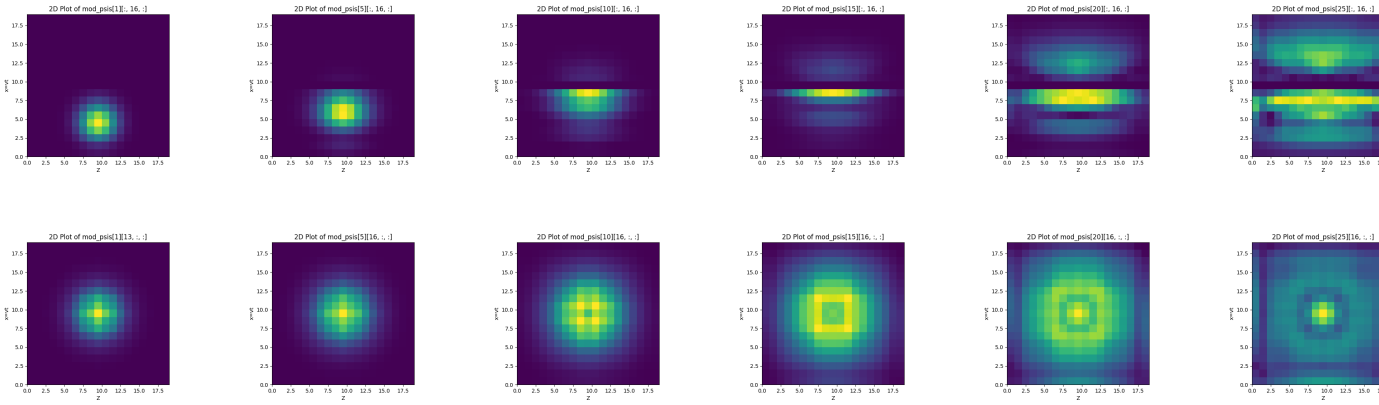


Figure 8: Circular Double Slit expt. Gaussian 3D Wavefront. Top row shows wave front is advancing and the probalility is spreading gradually. Bottom row shows evolution of fringe pattern with time.

determined trajectories). ψ does not have any source, nor affected by condition of particle. When $\psi \implies \eta\psi$ where η is a constant then quantum potential does not change with intensity of ψ but depends only on its form. A guided aeroplane moves according to the form of radio wave rather than its intensity.

In double slit expt. each electron has its own quantum field, but we choose those electrons that passes through any one slit. Deep valleys and broad plateaus are in Q distribution in space. where quantum potential changes rapidly, there is a strong force on the particle. The particle is deflected with V=0.

In double slit experiment, each photon has its own quantum field.

particle is at rest, $\nabla S = 0$ then quantun hamilton-jacobi is $E = V + Q$. Here E becomes constant, independent of any position.

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EDUCATION

7.2021 - till date **Bachelor of Engineering** at Jadavpur University at Kolkata, India
Focus on Computer Science, AI, Machine Learning
Expected graduation in June of 2025

2019 - 2021 **CBSE, Senior School Certificate** at Bhavan's G K Vidyamandir at Kolkata

2017 - 2019 **CBSE, Secondary School Exam** at Narayana School, Kolkata, India

WORK EXPERIENCE

2022 **HSF-India Training Event, conducted by Princeton University** at TIFR, India
The course focused on JAX in HEP, Scientific Python, and CUDA GPU Programming. JAX combines Autograd and XLA for high-performance machine learning research. It enables automatic differentiation of native Python and NumPy functions. Moreover, JAX can handle differentiation through loops, branches, recursion, and closures, and it can calculate derivatives of derivatives of derivatives. It supports both reverse-mode differentiation (a.k.a. backpropagation) and forward-mode differentiation effectively.

2023 **Open Source Contribution in C++ Library Automatic Differentiation** https://github.com/vgvassilev/clad

SKILLS AND QUALIFICATIONS

Programming Languages

Advanced skills Python, C, C++, CUDA
Basic skills Prolog, Qt, JavaScript, PHP

AI, Machine Learning

Advanced NVIDIA Jetson using OpenCV, Vision Transformer, Self-supervised Learning, SimCLR, RetNet, BYOL using pyTorch

Certifications

1. Programming Language with LLVM from Udemy
2. DSA Certificate from Geeks for Geeks
3. Summer School on Mathematical Foundation and ML, Jadavpur University
4. Introduction to Cloud Computing, IITKGP

Membership

1. IEEE, Computational Entelligence Society
2. IEEE, Computer Society
3. IEEE, Robotics and Automation Society

PROJECTS

2022 - till date **Project Completed** Project github: ShounakDas101

- Clang Automatic Differentiation: Clad enables automatic differentiation (AD) for C++. It is built on the LLVM compiler infrastructure and serves as a plugin for the Clang compiler. Clad employs source code transformation techniques. When provided with the C++ source code of a mathematical function, it automatically generates C++ code for computing derivatives of the function. As a contributor to this open-source project of CERN, Switzerland, I actively contribute to its development and improvement.
- Electron Photon Classification: This project involves exploring the application of convolutional neural networks, a category of Artificial Neural Networks within Deep Learning, to analyze data obtained from the Large Hadron Collider. The goal is to create a model capable of accurately classifying electron and photon electromagnetic showers by leveraging images captured by the detector in the dataset. The assessment of the model's performance will rely on metrics such as the Receiver Operating Characteristic curve (ROC) and the Area Under the ROC Curve score. Additionally, the development of deep models in Python will be facilitated by the Pytorch framework, a powerful library for this purpose.
- Co-VeGAN: Complex-Valued Generative Adversarial Network for Compressive Sensing MRI Reconstruction: The code for Co-VeGAN was written using the PyTorch library. However, the PyTorch library itself does not have the capacity to accept complex data directly. As a result, my assignment was to develop a code that could handle complex data as input and feed it to the Generative Adversarial Network without the need to separate the data into real and imaginary components.
- Cuda Programming on NVIDIA GPU: The NVIDIA CUDA Toolkit ver. 12 provides a development environment for creating high-performance GPU-accelerated applications. Utilizing the CUDA Toolkit, a multibody dynamics code has been developed, enabling the generation of complex chaotic patterns over time by a large number of interacting elements fixed in a 2D matrix.
- Embedded Image Processing using Jetson-Nano board: A series of actions is taken up, starting with flashing the Nano-board with a Jetpack using the SDK manager. Next, the NVIDIA Jetson Nano and coding environment are set up by installing prerequisite libraries and downloading DNN tools, including CUDA, Computer Vision, and Developer Tools. OpenCV is then installed, followed by the installation of the camera. Finally, a Python code is written for real-time object detection.
- Web based Human Machine Interface using JavaScript and PHP coding: In this project, analogue sensor data is acquired using an Arduino UNO board and transmitted to a PC through its serial port. The received serial data is then displayed on a webpage. Analog meters are also shown on the webpage, providing a user-friendly Human Machine Interface (HMI). The primary purpose of this system is to generate test results for the manufacturing of Token-less Block Instrument (TLBI), a railway signaling equipment.
- Development a mathematical and computational model of human decision-making using the Wayfinding theory, a process where individuals navigate through a complex space of possible actions. This project is to model how individuals make decisions when faced with limited time and cognitive resources, leading to choices that are formally sub-optimal yet resource-rational. For example, to develop a formal and computational model that captures these dynamics, we started with by formalizing a "choice" functional with sub-functionals representing priorities. Each priority sub-functional can then be weighted by an evolving activation function that activates a subset of priority sub-functionals at each timestep to simulate changing priorities. The application domain can be various scenarios such as market behavior, communicative interactions, or animal foraging