MODELING THE EXPLORATORY DYNAMICS OF THE INDIRECT PATHWAY IN THE BASAL GANGLIA USING A NETWORK OF CHAOTIC ATTRACTORS

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Introduction

- The basal ganglia (BG) are a group of subcortical structures deep within the cortex, consisting of four principal components: the striatum, globus pallidus (both externa and interna), substantia nigra (SN), and subthalamic nucleus (STN).
- BG play a vital role in both motor and non-motor functions, including reaching, gait, eye movements, speech, decision-making, and autonomic functions.
- They facilitate and inhibit movement through two primary pathways: the direct pathway (DP), which promotes movement, and the indirect pathway (IP), which inhibits unwanted motor activity.
- The DP is often referred to as the "Go" pathway, while the IP is termed the "No Go" pathway.
- Dopamine signaling from the substantia nigra pars compacta (SNc) is crucial in modulating the routing between these pathways. Loss of SNc neurons leads to dysfunctions like Parkinson's Disease (PD).
- Beyond pathway switching, SNc cell loss also affects the complexity of the IP, which is essential for exploration. Recent research over last decade or more emphasizes the STN's role in facilitating exploratory behavior, particularly in the context of PD.
- Our previous work has proposed that the BG can be modeled using principles of Reinforcement Learning (RL), where the DP is associated with exploitation and the IP with exploration.
- The STN's involvement in exploration is further supported by observed dynamics under PD conditions.
- In this study, we propose a model of the BG in which the complex dynamics of the STN-GPe circuitry are represented using a network of chaotic Rössler systems.

Equations

Computations at Striatum:

First the 'Input' is presented as the vector [1 1 1 1], the D1 striatum output that goes to the GPi is given as V_{D1_GPi} as shown in Eq. 1 below. The D2 striatum output reaching the GPi is denoted by V_{D2_GPi} as shown in Eq. 2.

$$V_{D1\_GPi} = Input\ .\ W_{DP}\ (\varepsilon) \quad (1)$$

$$V_{D2\_GPi} = Rossler(\epsilon, I_{STR\_GPe}) \quad (2)$$

$$where, I_{STR\_GP2} = Input. W_{STR_{GPe}}.(1-\epsilon) \quad (3)$$

$$\epsilon = \epsilon + \frac{1}{n_{actions}}\left[1 - \exp\left(-\frac{\delta^2}{\eta}\right) - \epsilon\right] \quad (4)$$

Q-learning and Weight Update:

$$Qval = \sigma(V_{D1\_GPi}) \quad (5)$$

$$\delta = Reward\ - Qval \quad (6)$$

$$W_{DP} = W_{DP} + \eta\delta \quad (7)$$

Simulating PD condition:

$$\delta = \min(\delta, \delta_{\text{lim}}) \quad (8)$$

Race Model

$$\frac{dV_{GPi}}{dt} = -V_{GPi} - d1_{amp}.V_{D1\_GPi} + d2_{amp}.V_{D2\_GPi} \quad (9)$$

Action selected = i^{th} card if $V_{GPi}^{i} > V_{threshold}; i = \{A, B, C, D\}$ (10)

Rossler System:

Equations (4),(5),(6) represents the dynamics of STN-GPe system defined by the function Rossler.

$$dx/dt = -y - z + k * (d - \bar{x}) \quad (10)$$

$$dy/dt = x + a * y \quad (11)$$

$$dz/dt = b + z * (x - c) + I_{STR\_GPe} \quad (12)$$

Model Architecture

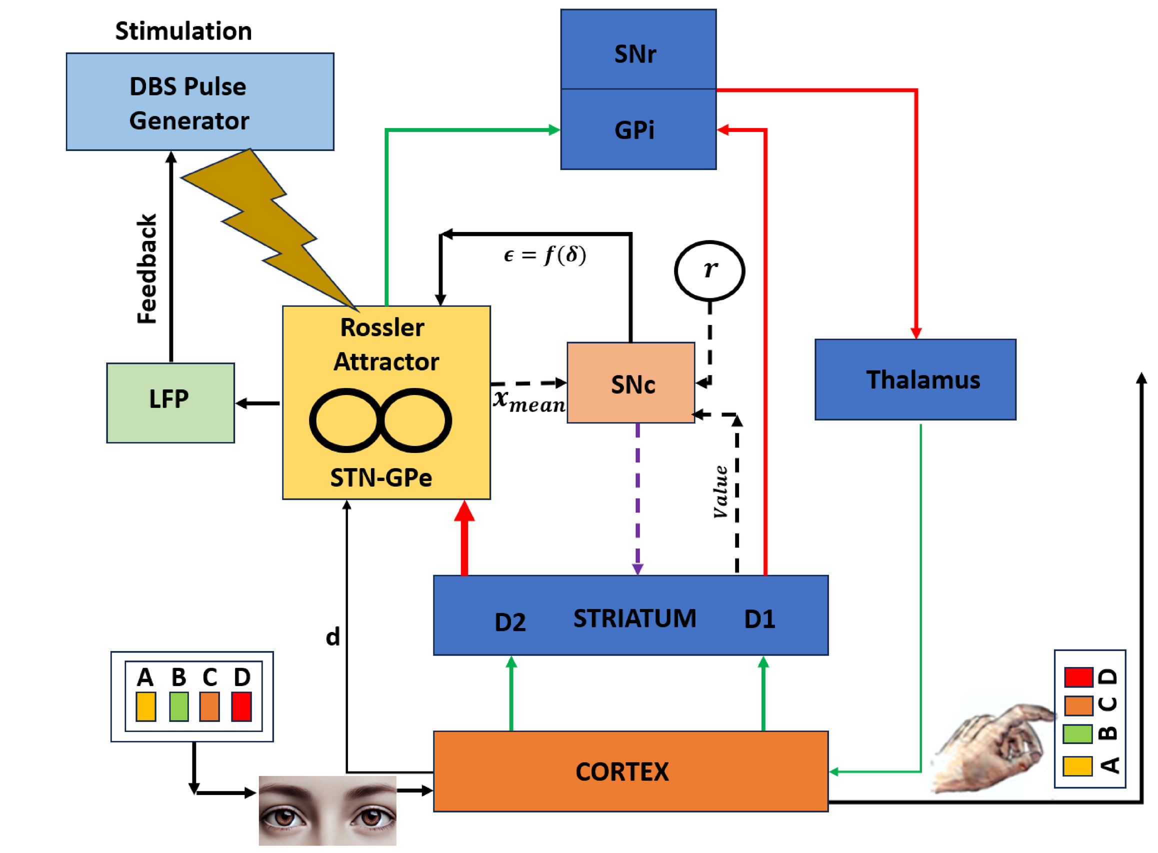

Figure 1. Model architecture of the BG circuitry used for IGT Task.

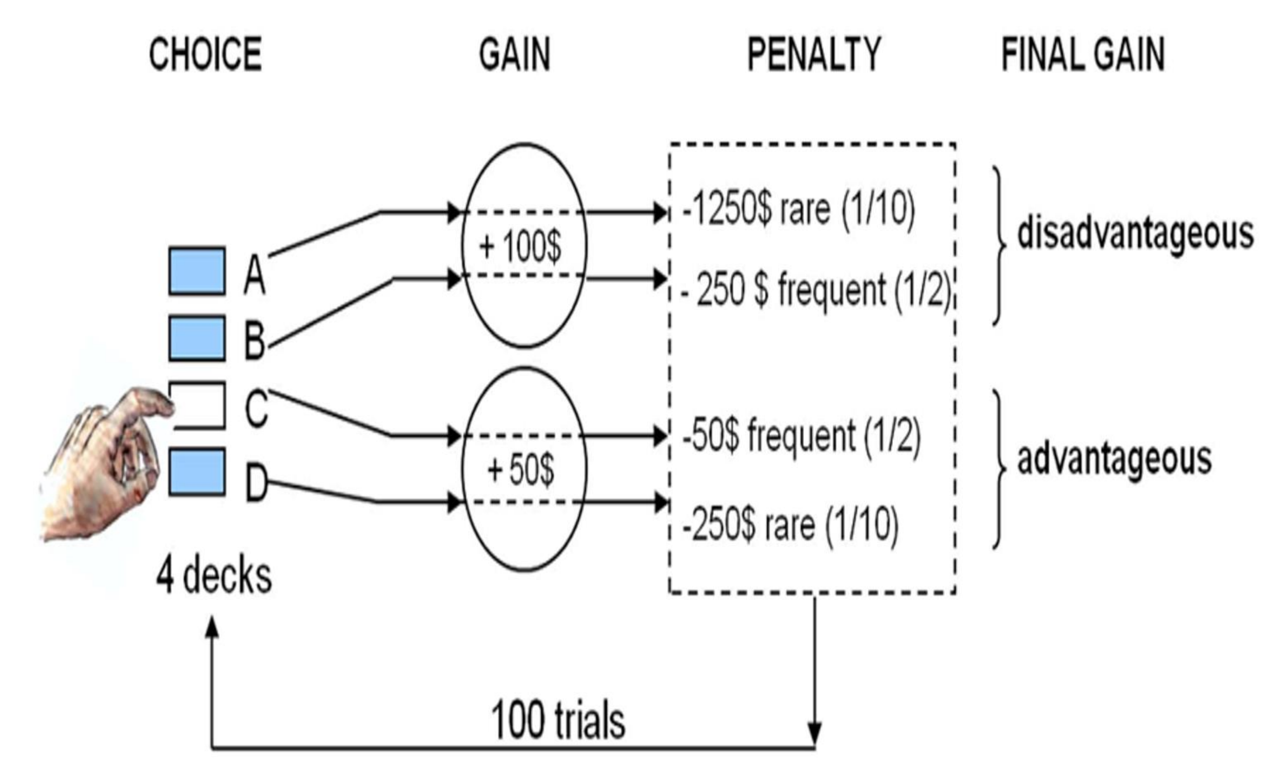

Figure 2. An Illustration of the IGT Task.

RESULTS

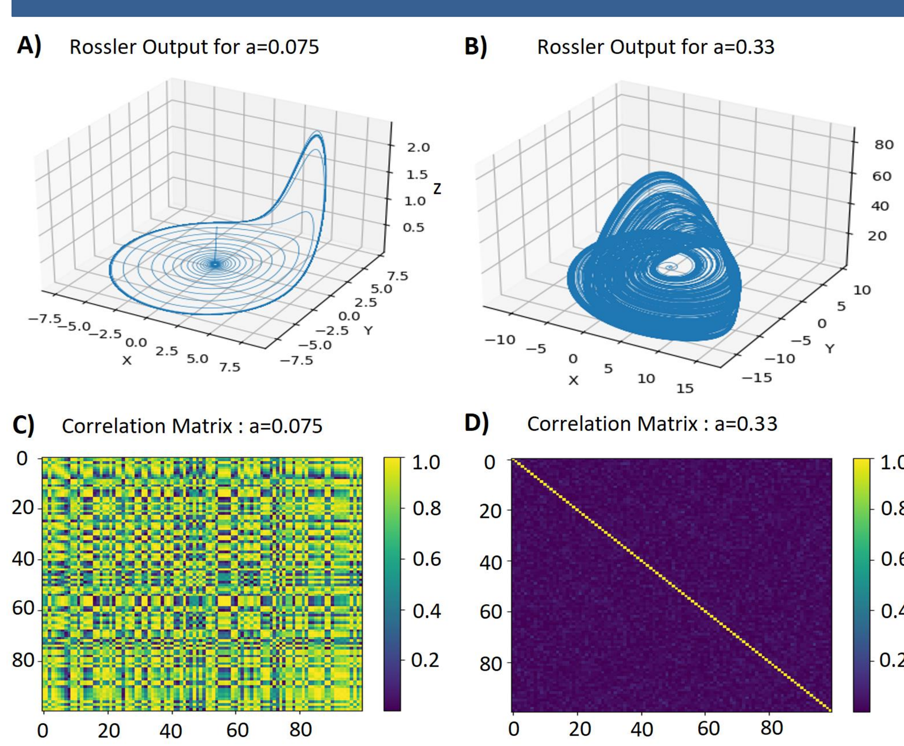

Figure 3. A) Output of the Rossler under periodic regime. B) Output of the Rossler under Chaotic regime. C) & D) Average pair wise correlation with a=0.075 and a=0.33.

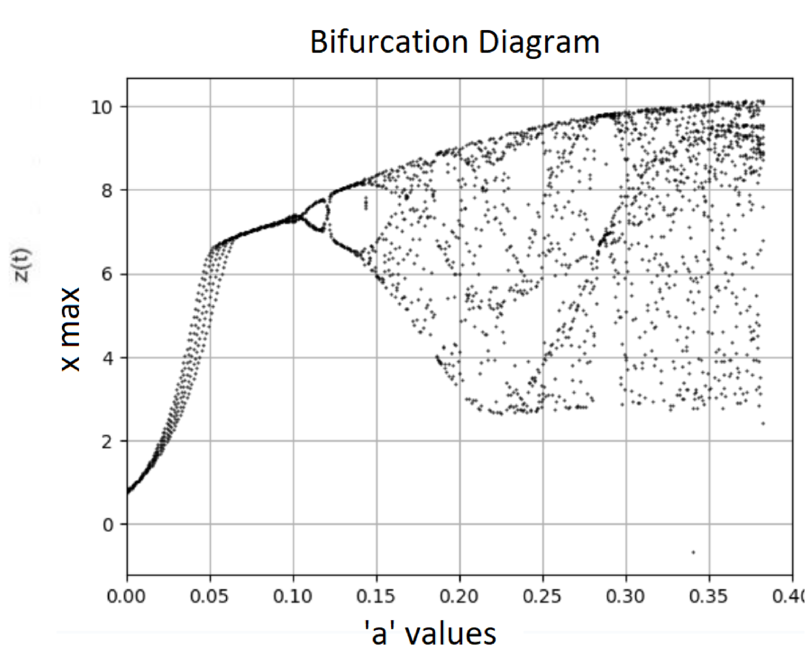

Figure 4. Bifurcation diagram of Rossler network with respect to variation in 'a'

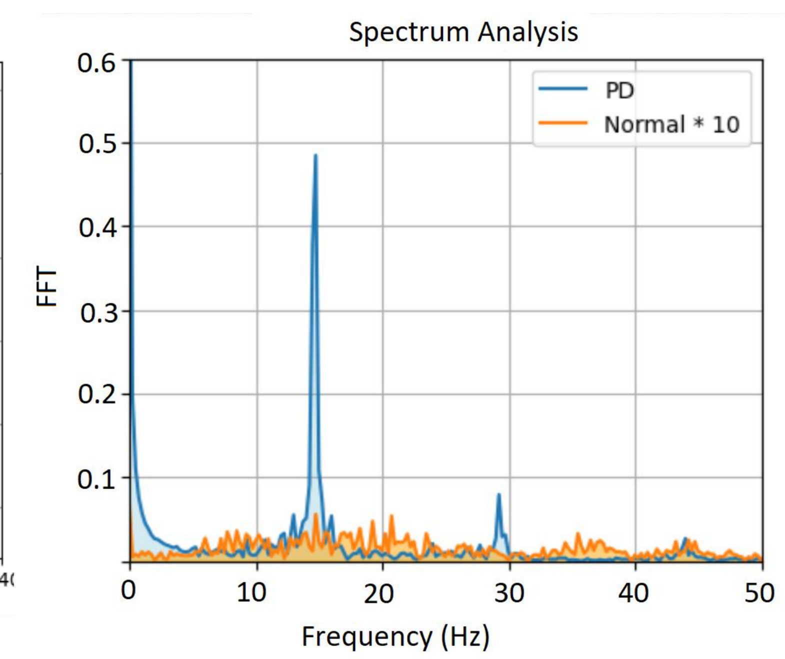

Figure 5. Frequency Spectrum of the LFP signal under normal and PD conditions

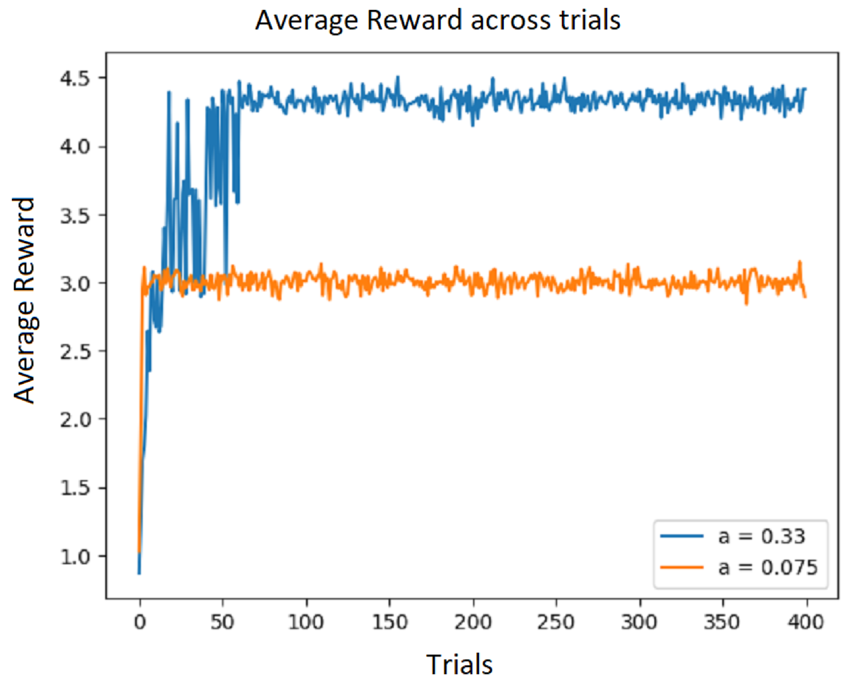

Figure 6: Average Reward over time for a 5-arm bandit task with varying values of 'a'.'

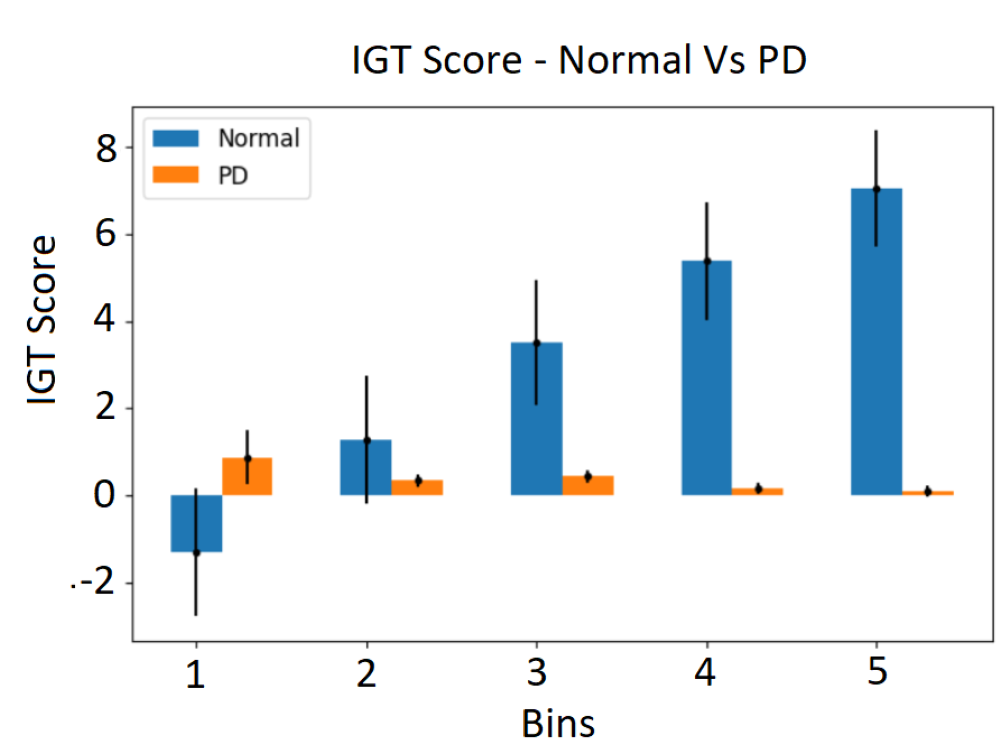

Figure 7. IGT score for Normal Vs. PD

IP Dynamics

- The dynamics of this network are adjustable through the parameter 'a,' enabling a transition from periodic to chaotic regimes, characterized by uncorrelated, desynchronized oscillations.
- In normal conditions, the network exhibits chaotic behavior, while it shows synchronized periodic oscillations under Parkinson's Disease (PD) conditions..
- The network receives feedback via mean-field diffusion from SNc, which controls the collective behaviour of the network as shown in Eq. 10.
- Temporal difference error (δ) is analogous to dopamine in SNc. We define epsilon (ε) as the exploratory parameter, which is a function of δ and linearly controls 'a' in the Rossler system as shown in Eq. 4.
- .This network also receives inputs (Iext) from the striatum (D2R neurons), which can induce STN transition into aperiodic regime (Eq. 12). The BG circuitry is trained for IGT using RL (Eq. 5-7).
- Under PD condition synchronous firing is observed among the neurons of the STN subsystem resulting in increased power in higher beta band frequencies.
- The initial stages of training demand a greater exploration (high ε), which necessitates the network to operate in a chaotic regime. To simulate the dopamine loss in PD condition, the δ value is delimited which in turn constrains ε,restricting STN to a periodic regime (Eq. 8).
- Dysfunctions of BG such as PD is simulated by modulating the incoming current arriving at the Rossler from Striatum as well as the 'a' parameter, which is analogous to the connectivity strength of the STN-GPe network.

Discussion

- Small changes in the starting conditions of certain systems can lead to highly unpredictable and complex behaviors, making long-term predictions difficult. This is often seen in chaotic systems, like weather patterns or certain ecosystems.
- In this study, we focused on the dysfunction in the basal ganglia (BG) circuitry and its crucial role in the manifestation of Parkinson's disease (PD) symptoms. The BG facilitates habit and procedural learning through a parallel process of exploration and value updating.
- We modeled the exploratory dynamics of the BG using a network of Rössler systems. By tuning parameters such as epsilon (ϵ) and the striatal current, we observed a transition of the STN-GPe dynamics from periodic to chaotic regimes (Fig. 3 A&B) .
- Specifically, lower values of ϵ corresponded to a periodic regime, while higher values resulted in chaotic behavior. This dynamic behavior significantly influenced the outcomes of our cognitive tasks, which included the multi-arm bandit and the Iowa Gambling Task (IGT).
- The bifurcation diagram (Fig. 4) illustrates how varying a particular parameter predicts the behavior of the chaotic system. We identified 'a' as the bifurcation parameter, governing the Rössler dynamics for values of a within the range a ∈ Q ∩ [0 , 0.4].
- Notably, 'a' is a function of ϵ, defining the model's level of exploration (indirect) versus exploitation (direct). Smaller values of 'a' corresponded to higher correlation coefficients (< 0.2), whereas larger values yielded lower correlations (0.2 to 0.37) due to chaotic dynamics (Fig. 3 C&D).
- We successfully modeled the STN-GPe dynamics using the Rössler attractor as an engine of exploration, replicating both normal and PD conditions. Validation of the STN-GPe model was achieved through the IGT task in both contexts, with PD group showing significantly lesser IGT scores (Fig. 7).
- Under PD conditions, we observed significantly higher power in the beta band of the local field potential (LFP) signal. The IGT scores increased across the bins for healthy controls in both experimental and model settings; however, this trend was not replicated in PD patients.
- In addition to the Iowa Gambling Task (IGT), we also modeled the multi-arm bandit task, observing variations in average reward as a function of different 'a' values. (a=0.33 results in a better average reward (Fig. 6).
- Looking ahead, we plan to incorporate deep brain stimulation (DBS) interventions within the Rössler model. Several studies are already exploring the oscillatory effects of stimulation pulses, and we believe this would be a valuable addition to our research, particularly in understanding the complex interactions between DBS and cognitive symptoms (Fig. 1).

ABBREVIATIONS

PD	Parkinson's Disease	IGT	Iowa Gambling Task
SNc	Substantia Nigra Pars Compacta	SN	Substantia Nigra
GPe	Globus Pallidus Externa	D1	D1 group of Medium spiny neurons(MSN)
GPi	Globus Pallidus Interna	D2	D2 group of Medium spiny neurons(MSN
STN	Subthalamic Nucleus	STN	Subthalamic Nucleus
STR	Striatum	Qval	Q value function
DP	Direct Pathway	LFP	Local Field Potential
IP	Indirect Pathway	BG	Basal Ganglia

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