The Fractal Propagation Model of Consciousness:

Unifying Time Perception and Memory Formation through RM Focus and Neural Plasticity

Abstract

We propose an extension of the Fractal-Based Consciousness Model (FBCM) by positing that both the subjective sensation of time and memory encoding emerge from a unified mechanism of fractal neural propagation. In our model, recursive neural activity propagates in self-similar (fractal) patterns, which generate the dynamic sensation of time and, when stabilized, encode memories. Crucially, the Reflective Manager (RM) modulates these propagation paths by focusing attention on specific content, thereby enhancing neural plasticity and promoting the stabilization—or "fixation"—of these paths as long-term memory traces. External sensory inputs calibrate this system, while internal factors such as metabolic constraints and heat dissipation modulate propagation speed. This framework provides testable predictions linking fractal metrics (e.g., Hurst exponent, box-counting dimension) to cognitive phenomena such as time distortion and memory fragmentation, and it offers promising applications in clinical interventions and AI architectures.

1. Introduction

Contemporary theories often treat time perception and memory as distinct processes, with time viewed as an external parameter and memory as static storage in synaptic weights. However, subjective experience suggests that time and memory are deeply intertwined, emerging from dynamic, self-organizing neural processes. Here, we extend the Fractal-Based Consciousness Model (FBCM) by proposing that:

- **Fractal propagation** in neural networks produces the continuous sensation of time.
- **Memory formation** is the result of certain propagation paths stabilizing via neural plasticity.
- The **Reflective Manager (RM)**—a mechanism for focused attention—selectively amplifies particular propagation sequences, thus enhancing their stabilization as memories.

By unifying these elements, our model explains phenomena such as time distortions during stress or isolation, as well as the vivid, dynamic nature of memory recall.

2. Theoretical Foundations

2.1 Fractal Propagation and Recursive Neural Dynamics

• Self-Similarity:

Neural activity exhibits fractal characteristics, where patterns observed in local circuits

repeat at multiple scales. This recursive propagation is essential for a dynamic and continuously evolving cognitive state.

• Emergent Time Perception:

Rather than relying on an external clock, the model posits that time perception arises from the rhythmic evolution of fractal propagation patterns. The rate and structure of these patterns—modulated by both external sensory inputs and internal metabolic constraints—determine the subjective experience of time.

2.2 Memory Encoding as Stabilized Propagation Paths

• Dynamic Encoding:

Memories are not stored as static entities but are encoded as stable, reactivatable propagation paths that emerge from initially divergent neural activity.

• Role of Neural Plasticity:

Repeated activation leads to synaptic changes (e.g., long-term potentiation) that consolidate these paths. The process of stabilization—or "fixation"—is greatly influenced by the RM's focused attention.

RM Focus:

The Reflective Manager acts as a selective amplifier. When the RM concentrates on a particular subject, it biases the propagation dynamics, making certain paths more likely to become stabilized and later reactivated during recall.

2.3 Modulation by External Inputs and Biological Constraints

• Sensory Calibration:

External stimuli calibrate neural propagation, maintaining a balanced divergence and convergence necessary for coherent time perception and memory formation. In the absence of such input (e.g., in isolation), the system can drift, leading to fragmented memories and altered time perception.

Metabolic and Thermal Regulation:

Neural firing is energetically demanding. The resulting heat dissipation, along with metabolic limits, naturally regulates the speed of propagation. Variations in these factors can lead to subjective distortions—such as time slowing under stress or speeding in focused states.

3. Mathematical Formalism

3.1 Recursive Propagation Equation

We represent the composite cognitive state at time step nn by a complex variable ZnZ_n (incorporating both reflective and automatic components). The updated state is given by:

 $Zn+1=\gamma RM \ tanh(softplus(Zn)+\mu Mn+An+DR)+\gamma APZn+\lambda En+\beta LL \ Le'vyn+\sigma \ \xi n.Z_{n+1} = \langle \{RM\}\} \ , \ tanh\ Big(\ \xi (Z_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta LL \ Le'vyn+\sigma \ \xi n.Z_{n+1} = \langle \{RM\}\} \ Z_n + \beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta LL \ Le'vyn+\sigma \ \xi n.Z_{n+1} = \langle \{RM\}\} \ Z_n + \beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta LL \ Le'vyn+\sigma \ \xi n.Z_{n+1} = \langle \{RM\}\} \ Z_n + \beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta LL \ Le'vyn+\sigma \ \xi n.Z_{n+1} = \langle \{RM\}\} \ Z_n + \beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta LL \ Le'vyn+\sigma \ \xi n.Z_{n+1} = \langle \{RM\}\} \ Z_n + \beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta LL \ Le'vyn+\sigma \ \xi n.Z_{n+1} = \langle \{RM\}\} \ Z_n + \beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta LL \ Le'vyn+\sigma \ \xi n.Z_{n+1} = \langle \{RM\}\} \ Z_n + \beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta LL \ Le'vyn+\sigma \ \xi n.Z_{n+1} = \langle \{RM\}\} \ Z_n + \beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta (\xi (X_n) + \mu M_n + A_n + D_R\) + \gamma APZn+\lambda En+\beta (\xi (X_n) + \mu M_n + \Delta_n +$

Explanation of Terms:

• ZnZ_n and Zn+1Z_{n+1}:

The current and subsequent cognitive states, representing the evolving neural propagation.

γRM tanh(·)\gamma_{\text{RM}} \, \tanh(\cdot):

The reflective component scaled by $\gamma RM \gamma_{RM} = {\text{RM}}$. The use of the hyperbolic tangent bounds the output, ensuring stability.

- **softplus(Zn)\text{softplus}(Z_n):** A smooth, non-linear transformation that prevents abrupt changes.
- μMn\mu M_n: Incorporates memory effects from past experiences.
- **AnA n:** Represents automatic, rapid processing.
- **DRD_R:** Reflects the fractal dimension of the propagation pattern, quantifying its complexity.

yAPZn\gamma_{\text{AP}} Z_n:

Propagates the existing state via automatic processing with gain $\gamma AP \gamma_{\gamma} = \gamma_{\gamma} \gamma_{\gamma}$.

• λEn\lambda E_n:

Introduces external sensory inputs into the dynamics, calibrating the internal propagation with the environment.

• β LL Le´vyn\beta_{\text{LL}}\, \text{Lévy}_n and σ ξ n\sigma\, \xi_n:

Model stochastic influences—rare, high-impact events via a Lévy process and routine Gaussian noise, respectively.

3.2 Integration of Biological Constraints

To incorporate biological modulation, an additional term can be introduced (e.g., βHHsync\beta_H H_{\text{sync}}) that captures how heat dissipation and metabolic rates affect neural synchronization. This term modulates the effective propagation speed, linking the internal dynamics directly with measurable biological processes.

4. Empirical Predictions and Experimental Design

4.1 Time Perception and Neural Synchronization

• Prediction:

Variations in external sensory input will alter the fractal propagation dynamics, thereby shifting subjective time perception.

• Experiment:

Conduct neuroimaging (EEG/fMRI) studies under conditions of controlled sensory deprivation versus enriched stimuli to correlate fractal metrics (Hurst exponent, boxcounting dimension) with reported time distortions.

4.2 Memory Formation and RM Focus

• Prediction:

Increased RM focus (as measured by prefrontal activation) will correlate with enhanced

neural plasticity and more robust stabilization of propagation paths, leading to stronger memory retention.

• Experiment:

Use tasks that demand focused attention and assess memory performance alongside measures of neural synchronization and fractal dynamics. Neurofeedback protocols could be used to actively modulate RM activity and test its effect on memory consolidation.

4.3 Metabolic Modulation

• Prediction:

Changes in neural metabolic rates and heat dissipation (via metabolic imaging or thermographic measures) should correlate with variations in propagation speed and subjective time perception.

• Experiment:

Manipulate metabolic state (e.g., via controlled physical exertion or pharmacological agents) and assess corresponding changes in EEG-derived fractal measures and behavioral reports of time perception.

5. Discussion

5.1 Integration with Existing Theories

Our model unifies aspects of spiking neural network theory, fractal dynamics, and synaptic plasticity. Unlike static storage models, it emphasizes that memories and time perception are dynamic, continuously evolving phenomena. The RM's role in selectively focusing neural propagation provides a concrete mechanism linking attention to memory consolidation—a concept supported by recent neuroimaging studies.

5.2 Clinical and AI Implications

• Neuropsychiatric Disorders:

Disrupted propagation dynamics may underlie conditions such as ADHD, PTSD, or Alzheimer's disease. Interventions that restore balanced propagation—via neurofeedback or sensory stimulation—could improve cognitive function.

Artificial Intelligence:

Incorporating fractal propagation and dynamic stabilization mechanisms into AI architectures may yield systems with more human-like temporal processing and memory formation.

5.3 Limitations and Future Directions

• Biological Mapping:

Further research is needed to concretely map abstract parameters (e.g., $\gamma RM,DR \gamma_{k}, D_{k}, D_{k$

• Experimental Validation:

The model generates numerous testable predictions. Future work must design rigorous

experiments to validate the relationship between fractal propagation metrics, RM focus, metabolic modulation, and cognitive outcomes.

• Interdisciplinary Collaboration:

Progress will benefit from collaborations among neuroscientists, physicists, and computational modelers to refine the framework and integrate it with existing theories of consciousness and cognition.

6. Conclusion

The Fractal Propagation Model of Consciousness posits that the dynamics of self-similar, recursive neural propagation are the underlying substrate for both time perception and memory formation. External sensory inputs and internal factors—most notably the selective focus of the Reflective Manager and biological constraints like heat dissipation—modulate these propagation dynamics. By linking the stabilization of propagation paths to memory encoding and framing time perception as an emergent property of these dynamics, the model offers a unified, testable framework that challenges traditional static models of cognition. This paradigm not only advances our theoretical understanding but also paves the way for innovative applications in clinical treatment and artificial intelligence.

References

- 1. Tononi, G., & Koch, C. (2015). Consciousness: Here, There and Everywhere? *Philosophical Transactions of the Royal Society B: Biological Sciences*, *370*(1668), 20140167.
- 2. Baars, B. J. (1997). *In the Theater of Consciousness: The Workspace of the Mind*. Oxford University Press.
- 3. Husserl, E. (1928). *The Phenomenology of Internal Time-Consciousness*. Indiana University Press.
- 4. Whitehead, A. N. (1929). Process and Reality. Macmillan.
- 5. Varela, F. J., Thompson, E., & Rosch, E. (1991). *The Embodied Mind: Cognitive Science and Human Experience*. MIT Press.
- 6. Mandelbrot, B. B. (1982). The Fractal Geometry of Nature. W.H. Freeman.
- 7. Costa, M., Goldberger, A. L., & Peng, C.-K. (2002). Multiscale Entropy Analysis of Complex Physiologic Time Series. *Physical Review Letters*, 89(6), 068102.
- 8. Additional studies on spiking neural networks, fractal metrics in EEG/fMRI, and neuroplasticity literature as relevant.