Research Proposal

Toward Trustworthy and Noise-Aware Graph Intelligence

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1. Background and Research Gap

In recent years, the intersection of stochastic dynamics and intelligent learning systems has attracted increasing attention across fields ranging from signal processing to artificial intelligence. Stochastic resonance (SR) theory demonstrates that noise, traditionally regarded as a detrimental factor, can instead play a constructive role in amplifying weak signals under suitable nonlinear or stochastic conditions [1–3]. Building upon this foundation, Generalized Stochastic Resonance (GSR) extends the applicability of conventional SR to both linear [4] and coupled systems [5, 6], enabling noise-assisted feature enhancement and stabilization under complex conditions. Subsequent studies introduced optimization frameworks based on theoretical performance metrics [7, 8] to systematically regulate resonance behaviors. Recently, I extended the synchronization mechanism from coupled stochastic resonance networks to the GSR framework by incorporating first- and second-order stochastic asymptotic stability constraints, resulting in a Robust-GSR system[9]. Compared with conventional approaches that require multiple averaging iterations to achieve optimal performance, the proposed system attains the optimal output in a single iteration, substantially improving the stability and computational efficiency of the resonance process.

Recent studies have introduced SR into neural network design, demonstrating that controlled noise can enhance robustness and generalization by stabilizing weak feature responses. For instance, Fu et al. [10] showed that SR-based spiking neural networks improve visual perception by amplifying low-contrast signals, while Manuyovich et al. [11] developed SR-driven neurons that reduce sensitivity to noise perturbations and improve learning stability in deep models. These findings highlight the constructive role of noise in enhancing neural dynamics and inspire the integration of SR into modern architectures. However, existing research remains limited to feedforward and convolutional structures, with no systematic exploration of SR within graph neural networks (GNNs), where message propagation and topological uncertainty make noise utilization particularly promising for achieving robustness and interpretability.

Meanwhile, GNNs have emerged as a powerful framework for learning from relational and multimodal data [12, 13]. However, their success is often constrained by structural perturbations, noisy node signals, and skewed label distributions. Although recent advances in spectral graph learning have provided fresh insights into frequency-domain representations and filtering mechanisms [14], applying these spectral approaches to dynamic, heterogeneous, or evolving graph structures remains a major challenge. Moreover, while contrastive and diffusion-based learning methods emphasize the geometry and uniformity of latent representations, the interaction between stochastic dynamics and representation geometry in graph domains is still poorly understood.

In parallel, the advent of large language models (LLMs) and multimodal LLMs (MLLMs) has broadened representation learning from unimodal text or vision to integrated reasoning across modalities [15–18]. Despite their impressive zero/few-shot capabilities, these models typically rely on massive pretraining data and compute, and they can be brittle under dataset shift and noisy or low-resource conditions; moreover, hallucination and instability of latent representations remain open concerns for trustworthy deployment [19, 20].

2. Research Motivation

Motivated by these gaps, this research aims to bridge SR theory with deep and graph-based learning frameworks to construct robust, interpretable, and noise-aware multimodal representation models. The central idea

is to exploit the constructive role of stochastic dynamics—specifically, the self-adaptive coupling and energy transfer mechanisms of SR—to enhance the stability, diversity, and reliability of learned representations. By embedding resonance-driven dynamics into graph architectures, the proposed approach seeks to regulate information propagation through controlled stochasticity, thereby mitigating representation collapse, improving generalization under distributional shifts, and promoting physically grounded interpretability.

From a theoretical perspective, this study will formalize the interaction between stochastic coupling and graph spectral geometry, providing a unified view that connects nonlinear resonance theory with message-passing and diffusion-based learning. On the algorithmic level, it will develop modular frameworks that integrate noise-adaptive mechanisms into multimodal graph models, enabling dynamic adaptation to uncertainty, heterogeneity, and evolving topologies. Ultimately, this research aims to advance the foundation of trustworthy graph intelligence—AI systems that remain stable, interpretable, and resilient even under low-resource or noisy environments.

3. Research Objectives and Key Questions

3.1. Research Objectives

This research aims to develop a unified framework that bridges *stochastic resonance* (SR) dynamics with *graph-based and multimodal representation learning*, enhancing robustness, interpretability, and adaptability in modern AI systems. Unlike traditional SR applications limited to vibration or low-dimensional signals, this work extends SR principles to high-dimensional and heterogeneous data—including **time-series signals**, **low signal-to-noise ratio (SNR) images**, and **language-model-derived embeddings**. The specific objectives are as follows:

(1) **Develop Noise-Aware Graph Learning Models for Multimodal Data:** Integrate stochastic stability and resonance mechanisms into graph neural networks (GNNs) to improve representation reliability across diverse modalities. Each node may encode a one-dimensional time series, an image patch, or a text embedding (e.g., from BERT or GPT), enabling noise-driven feature amplification that enhances semantic robustness and cross-modal consistency.

(2) **Design Adaptive Spectrum-Aware Mechanisms for Dynamic Graphs:** Extend the Robust-GSR framework toward spectral and diffusion-based graph learning, allowing the model to dynamically regulate frequency components according to the modality or noise statistics of each node—thus improving adaptability in non-stationary, multimodal graphs.

(3) **Establish Hypergraph Resonance for Collective Multimodal Reasoning:** Generalize SR to hypergraph structures to model higher-order semantic or sensory relationships. Each hyperedge can represent a "resonant cluster" linking multimodal nodes (e.g., text–image–signal triplets), supporting cooperative amplification of weak correlations and fostering richer cross-domain representations.

(4) **Enable Causal and Physically Interpretable Graph Modeling:** Assign physical meaning to graph edges by modeling them as stochastic couplings whose conductance depends on modality similarity, node phase difference, and contextual noise. This provides a dynamical explanation for how and why information propagates across modalities, contributing to trustworthy and interpretable graph reasoning under distributional shifts.

3.2. Key Scientific Questions

This research seeks to address several core questions at the intersection of stochastic dynamics, graph representation learning, and large language model (LLM) integration:

Q1. **How can stochastic resonance dynamics enhance multimodal representation learning?** Can noise-driven amplification mechanisms stabilize embeddings derived from pretrained language or vision models?

Q2. **How can adaptive spectral mechanisms improve robustness in non-stationary multimodal graphs?** Is it possible to modulate spectral energy across modalities to suppress noise while preserving shared semantics?

Q3. **How do resonance interactions emerge in hypergraphs for collective reasoning?** Can stochastic coupling explain how weakly correlated multimodal nodes jointly contribute to high-level semantic decisions?

Q4. **How can SR-based dynamics improve the interpretability and reliability of GNNs under LLM-augmented settings?** Can we build physically grounded causal pathways that explain decision consistency across text, vision, and signal domains?

4. Proposed Research and Methodology

Building upon the key scientific questions outlined above, this section presents the proposed research methodology across four interrelated directions. Each direction is designed to progressively extend the theoretical foundation of stochastic resonance (SR) into practical graph and multimodal learning frameworks, bridging physics-inspired dynamics with modern representation learning.

4.1. Direction 1: Noise-Aware Graph Learning Models for Multimodal Data

Motivation. Existing graph neural networks (GNNs) often struggle to maintain stable and discriminative representations under noisy, small-sample, or heterogeneous input conditions. Inspired by stochastic resonance (SR), where moderate noise enhances weak signals, this work seeks to explore how noise-driven amplification can stabilize and enrich multimodal embeddings, including time-series, image, and language-model-derived representations.

Methodology. We will incorporate SR-inspired dynamic perturbations into graph contrastive learning, where each node may represent a signal sequence, an image patch, or a text embedding. The method will introduce noise-modulated feature amplification modules that learn optimal stochastic intensity to maximize inter-class separability while preserving intra-class consistency. We will evaluate this approach on multimodal benchmarks, including textual-visual datasets and sensor–language fusion corpora.

Expected Outcomes. This study is expected to yield a noise-adaptive contrastive framework capable of maintaining robust multimodal representations and mitigating representation collapse, even when pretrained embeddings (e.g., BERT, GPT) are degraded by noise or domain shift.

4.2. Direction 2: Adaptive Spectrum-Aware Mechanisms for Dynamic Graphs

Motivation. Spectral graph learning provides a frequency-domain view of node interactions but remains limited by static filters that cannot adapt to time-varying or modality-dependent noise. The generalized stochastic resonance (GSR) theory offers a foundation for dynamic frequency response optimization through multiplicative noise regulation.

Methodology. We propose an adaptive spectral graph network that integrates the Robust-GSR mechanism as a frequency-domain controller. By learning to modulate spectral energy across graph Laplacian eigenmodes, the model can adaptively enhance informative frequencies and suppress noise-induced artifacts. This will be extended to multimodal graphs, where each modality contributes distinct spectral signatures.

Expected Outcomes.. We anticipate enhanced robustness and adaptability in dynamic and heterogeneous graph environments, particularly in multimodal contexts such as video–text fusion or time-varying sensor networks. The findings will demonstrate how stochastic resonance principles can support self-regulating spectral adaptation mechanisms, enabling graph learning models to adjust dynamically to evolving data distributions.

4.3. Direction 3: Hypergraph Resonance for Collective Multimodal Reasoning

Motivation.. Real-world data interactions often transcend pairwise relations, forming higher-order dependencies among modalities (e.g., text–image–audio triplets). Conventional GNNs cannot efficiently model these multi-way interactions or the cooperative enhancement that emerges under weak correlation.

Methodology.. We will construct a hypergraph stochastic resonance model in which each hyperedge functions as a "resonant cluster" that dynamically couples multiple modalities. Using nonlinear stochastic dynamics, the system will identify and amplify weak yet semantically relevant cross-modal relationships. A graph-to-hypergraph transformation module will be developed to jointly optimize pairwise and higher-order representations.

Expected Outcomes.. This study will provide a novel computational interpretation of collective intelligence and cooperative perception, enabling more accurate and explainable reasoning in multimodal learning and few-shot inference scenarios.

4.4. Direction 4: Dynamic Subgraph Modeling for Causal Interpretability

Motivation.. While GNNs effectively capture statistical correlations, they often lack causal interpretability, leaving open the question of *why* information propagates along certain edges. Embedding stochastic resonance dynamics into edge modeling offers a physically grounded means to interpret these propagation patterns.

Methodology.. We will model graph edges as dynamic stochastic couplings whose conductance states depend on node similarity, phase difference, and local noise. By analyzing energy transfer pathways induced by SR mechanisms, we will derive causal subgraph structures that reflect physically meaningful information flow. The framework will be evaluated under out-of-distribution and adversarial perturbations to assess reliability and interpretability.

Expected Outcomes.. This direction is expected to yield a new paradigm of physically interpretable and causally grounded GNNs, bridging dynamical systems theory and trustworthy AI. It will enable robust decision consistency across modalities (text, vision, and signals), contributing toward explainable and reliable multimodal reasoning.

5. Expected Contributions and Potential Impact

This research is expected to establish a unified theoretical foundation connecting stochastic dynamics and multimodal representation learning. By formalizing stochastic resonance (SR) and generalized stochastic resonance (GSR) within the context of graph-based learning, it will provide new insights into how controlled noise can enhance feature stability, information propagation, and representation geometry. The resulting theoretical

models will contribute to the broader understanding of noise-assisted learning mechanisms and the dynamics of self-organized feature adaptation in neural networks.

Methodologically, this work will introduce several innovative components: (1) a noise-aware contrastive learning framework that adaptively regulates stochastic intensity for robust multimodal embeddings; (2) a spectrum-aware graph architecture that dynamically modulates frequency responses via the Robust-GSR mechanism; (3) a hypergraph resonance model that captures higher-order interactions and cooperative signal amplification across modalities, providing a unified representation space for cross-modal reasoning and collective decision-making; and (4) a physically interpretable GNN framework that models edges as dynamic stochastic couplings, bridging causal reasoning with data-driven representation learning. These components will serve as modular tools for constructing more reliable and explainable graph-based AI systems.

From an application perspective, the proposed framework will advance robust and trustworthy learning across multiple domains, including multimodal reasoning, knowledge graphs, and large language model (LLM)–augmented systems. By improving stability under noise, heterogeneity, and data scarcity, the research outcomes can enhance performance in safety-critical tasks such as autonomous perception, medical diagnosis, and financial risk monitoring. Furthermore, the physical interpretability introduced by SR-based dynamics can help bridge the gap between black-box AI and transparent, human-understandable decision-making. Ultimately, this work aims to contribute toward the development of a new generation of **trustworthy, physics-informed, and noise-resilient intelligent systems**.

6. Research Plan

The proposed research will be carried out over four years, following a progressive schedule that integrates theoretical analysis, model development, and large-scale empirical validation. Table 1 summarizes the key milestones and deliverables for each phase.

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Table 1: Four-Year Research Plan and Milestones

Year	Phase	Key Objectives and Tasks
Year 1	**Theoretical Foundation and Preliminary Experiments**	• Formulate mathematical foundations for GSR and Robust-GSR in graph learning. • Analyze noise-induced stability and spectral modulation mechanisms. • Conduct small-scale multimodal experiments (e.g., time-series, image–text pairs). • Prepare an initial conference paper draft on GSR-based feature enhancement.
Year 2	**Model Development and Algorithmic Integration**	• Develop noise-adaptive contrastive and spectrum-aware graph learning modules. • Introduce a hypergraph resonance framework for modeling higher-order multimodal relations. • Evaluate the proposed models on benchmark datasets (Conceptual Captions, Flickr30K, multimodal sensor sets). • Disseminate research findings through peer-reviewed publications and academic conferences.
Year 3	**Causal Modeling and Large-Scale Validation**	• Develop physically interpretable GNNs incorporating stochastic coupling dynamics. • Integrate embeddings from large language models (e.g., CLIP, LLaMA, GPT) for cross-modal learning. • Conduct ablation and robustness analyses under noisy and imbalanced conditions. • Complete large-scale validation and comparative experiments
Year 4	**Consolidation and Dissemination**	• Synthesize findings into a unified Robust-GSR-GNN theoretical framework. • Prepare comprehensive journal and thesis manuscripts summarizing theoretical and experimental outcomes. • Open-source the developed frameworks with documentation and reproducible benchmarks. • Present research achievements at international academic conferences.

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