Spin-Resonant Geometric Intelligence (SRGI): Unifying Geometry, Resonance, and Neural Computation for Scalable Intelligence

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Abstract

Transformer-style large language models (LLMs) excel at sequence modeling but remain brittle on persistent memory, long-horizon reasoning, and self-consistent state evolution. We propose **Spin-Resonant Geometric Intelligence (SRGI)**, a physics- and neuroscience-inspired architecture that augments LLMs with (i) geometric latent structure on curved manifolds to encode hierarchy and periodicity, (ii) resonant state dynamics (phase-aware, lightly damped oscillations) to preserve information and enable selective routing, and (iii) spinor/symmetry-aware representations to stabilize relational reasoning. SRGI is designed as a practical fork over compact LLMs (e.g., NanoChat-class) with drop-in modules: complex/quaternion spinor embeddings, unitary/orthogonal resonance-preserving layers, phase-aware attention, hyperbolic+toroidal bottlenecks, and attractor memory heads (modern Hopfield-style). We detail motivations from physics (geometry, resonance, Berry phases) and brain dynamics (coherence, phase-locking, attractors), formalize the core mechanisms, and lay out training, evaluation, and ablation plans. We argue SRGI advances the field by offering structure over scale: sustained context without external retrieval, reduced hallucination via attractor stability, and more transferable relational abstractions via group-equivariance. We provide concrete implementation notes and reproducible benchmarks to stress memory, binding, and planning.

1 Introduction

LLMs have delivered striking capabilities in language, code, and tool use, yet they show context fading, inconsistent self-reference, and fragile reasoning. Most remedies—longer context windows, better KV caching, or retrieval augmentation—treat memory as an external prosthesis rather than a native computational property. Meanwhile, biological systems achieve persistent, selective communication via oscillations and phase-synchrony; attractor networks support stable, re-enterable states that feel like "thoughts"; and cortical geometry favors hierarchy and efficient routing.

Hypothesis. Endowing neural networks with geometric state spaces, resonant dynamics, and symmetry-aware representations yields: (1) longer true memory (without bloated context), (2) cleaner binding and multi-entity reasoning (via phase), (3) more stable relational generalization (via spin/equivariance), and (4) lower hallucination through attractor-constrained decoding.

Contributions.

1. **Architecture.** SRGI augments a Transformer with: spinor (complex/quaternion) embeddings; unitary/orthogonal resonant layers; phase-aware attention; hyperbolic+toroidal latent bottlenecks; and complex Hopfield-like attractor memory.

2. **Theory.** We align mechanisms with physics (geometry/resonance/Berry phase) and neuroscience (communication-through-coherence, phase–amplitude coupling, attractors).

3. **Math & Training.** Gradual formalization, stability constraints (spectral/unitary), phase-consistency and attractor objectives.

4. **Evaluation.** A reproducible suite emphasizing memory stability, binding, planning, and long-range credit assignment.

5. **Ablations.** Clear tests to distinguish gains from scale vs. structure.

2 Background & Motivation

2.1 Geometry as Computation Substrate

- Curvature encodes structure. Hyperbolic spaces efficiently embed trees/hierarchies; toroidal components capture periodic/phase phenomena. Prior ML shows hyperbolic embeddings compactly represent taxonomies and entailments compared to Euclidean spaces.

- Why LLMs benefit. Syntax/knowledge graphs are hierarchical; long-range periodicities (topic cycles, meter) are naturally toroidal. Embedding states in $\mathbb{H}^d \times \mathbb{T}^k$ provides stable basins (hyperbolic) with phase continuity (tori).

2.2 Resonance & Phase for Memory and Routing

- Oscillations preserve energy/information. Unitary/orthogonal updates keep norms, mitigating vanishing/exploding signals (a classical issue in RNNs and long contexts).

- Phase-based communication. In brains, coherence selects partners: "in phase, we talk"; out of phase, we're effectively gated. Bringing phase-aware attention to LLMs biases binding toward phase-aligned tokens/spans.

2.3 Spin & Symmetry for Relational Stability

- Spinors (complex/quaternion representations) carry orientation and chirality, and group-equivariant mappings preserve structure under transformations (e.g., SU(2) rotations).

- Why LLMs benefit. Many reasoning tasks implicitly require role/orientation invariance (A-before-B, subject/object role swaps). Equivariance limits hypothesis space, improving systematic generalization.

3 Related Work (selective)

- Transformers & long context. Vaswani et al. (2017); rotary position embeddings (RoPE); state-space models (S4/Hyena).

- Unitary/orthogonal dynamics. Unitary/orthogonal RNNs; Householder/Givens parametrizations.

- Hyperbolic learning. Poincaré embeddings, Riemannian optimization.
- Complex/quaternion nets. Complex-valued NNs and quaternion NNs.
- Modern Hopfield networks. Energy-based associative memory.
- Neuroscience inspirations. Communication-through-coherence (CTC), cross-frequency coupling, attractor dynamics.

(Full citations in §12.)

4 SRGI Architecture

SRGI is a stacked, residual architecture compatible with existing Transformers. Each block adds three orthogonal biases:

1. **Spinor Embeddings (SE).** Replace real embeddings with complex/quaternion channels. Represent token x as $z = a + ib$ (or quaternion). Linear maps constrained to unitary/orthogonal factors.
2. **Resonant State-Space Layer (R-SSM).** Selective SSM with eigenvalues near the imaginary axis ($\Re(\lambda) \approx 0$). Cross-band coupling implements phase–amplitude interactions.
3. **Phase-Aware Attention (PAA).**

   $$\alpha_{ij} \leftarrow \alpha_{ij}\big(1 + \beta\cos(\phi_i - \phi_j)\big),$$

   where ϕ are per-token phases.
4. **Geometric Bottleneck (GB).** Project channels into $\mathbb{H}^d$ (Poincaré ball) and $\mathbb{T}^k$.
5. **Attractor Memory Head (AMH).** Modern Hopfield-style over complex keys; 1–3 inner iterations at inference.

Block order (per layer):
Spinor Linear → R-SSM (residual) → Phase-Aware Attention → MLP → Geometric Bottleneck → (optional) Attractor read → Residual & LayerNorm.

5 Mathematical Formulation (light, essential)

5.1 Spinor/Unitary Mappings

Parametrize unitary U as product of Givens rotations to ensure $\|Uz\|_2 = \|z\|_2$.

5.2 Resonant SSM

Continuous-time SSM with $\Re(\lambda) \approx 0$. Cross-frequency coupling:

$$\phi_{\text{fast}} \leftarrow \phi_{\text{fast}} + \alpha\sin(\phi_{\text{slow}} - \phi_{\text{fast}}).$$

5.3 Phase-Aware Attention

$$s_{ij} = \frac{\tilde{q}_i^\top \tilde{k}_j}{\sqrt{d_k}} \cdot \Big(1 + \beta\cos(\phi_i - \phi_j)\Big).$$

5.4 Hyperbolic/Toroidal Bottleneck

Use $\exp_0^c/\log_0^c$ maps for hyperbolic; angles mod 2π for torus.

5.5 Attractor Memory

Modern Hopfield energy over complex keys:

$$E(z) = -\log \sum_m \exp\left(\Re(z^\dagger K_m)\right).$$

6 Objectives & Regularization

Primary: cross-entropy. Additional: phase-consistency, geometric topology, spectral/unitary constraints, attractor stability.

7 Implementation Plan (NanoChat-class fork)

Phase-1 (minimal): complex embeddings, unitary layers, one R-SSM, phase-aware attention.
Phase-2: hyperbolic+toroidal bottleneck, complex Hopfield.
Phase-3: scaling, instruction tuning, long-context curriculum.

FLOPs overhead bounded to 1.3–1.6×.

8 Evaluation Suite

- **Memory & Continuity:** NIAH 128k, long anaphora, consistency drift.
- **Binding & Reasoning:** multi-entity transformations, Dyck languages, multi-hop QA.
- **Planning & Tool Use:** ReAct loops, tool chaining.
- **Robustness:** TruthfulQA, hallucination reduction.
- **Ablations:** module-by-module gains vs. parameter-matched baselines.

9 Safety, Alignment, and Interpretability

Phase dashboards, attractor auditing, geometric lenses, temperature-phase desynchronization.

10 Limitations & Risks

Training stability, compute overhead, attractor mis-binding.

11 Reproducible Research Plan

Open repository (Apache-2.0), unit tests, checkpoints, failure cases.

12 References (selected)

13 Why SRGI Will Move the Field Forward

1. Structure over scale
2. Native memory
3. Cleaner reasoning
4. Systematic generalization
5. Interpretability hooks
6. Engineering realism

14 Conclusion

SRGI reframes LLMs as structured dynamical systems: information flows on curved manifolds, resonates through phase-coherent channels, and settles into associative attractors that stabilize thought. This union of geometry, resonance, and spin/symmetry offers a concrete path to longer memory, cleaner reasoning, and safer outputs—advances that matter more than another doubling of parameters.

A Practical Build Notes

Libraries, initialization, curriculum, metrics, ablation order.

B Proposed Public Benchmarks

SRGI-Mem-Suite, SRGI-Bind-Suite, SRGI-Plan-Suite, SRGI-Safety-Suite.

End of draft.