Frictional Interaction Fields (FIF):
A Symmetric Energy-Based Inductive Bias for Robust Multi-Modal Integration

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Draft Version 0.2 — Conceptual Prototype Only

Abstract

We introduce **Frictional Interaction Fields (FIF)**, a symmetric, energy-based inductive bias that models cross-channel disagreement as physical *friction*. Unlike attention, which relies on asymmetric similarity weighting, FIF penalizes inconsistency between modalities through an energy minimization process, yielding equilibrium representations rather than attention-weighted averages. We present both continuous and discrete formulations, highlight its relation to Laplacian energy, anisotropic diffusion, and gradient flow, and discuss how external task constraints act as multidimensional pressures. A toy-level prototype suggests that FIF produces a frictional energy metric linearly correlated with task conflict and exhibits improved stability under synthetic noise. This paper serves as an early conceptual report.

1 Introduction

Attention mechanisms dominate contemporary deep architectures by focusing on similarity-based relevance between features. However, when modalities conflict, such asymmetric focusing fails to capture the *cost of disagreement*. We propose FIF, where the system seeks equilibrium by dissipating internal tension. Intelligence here is not the art of selecting importance but of balancing contradictions.

Our contributions:

1. A symmetric, energy-driven coupling mechanism replacing probabilistic weighting.
2. A unified view over continuous fields, discrete graphs, and sequences.
3. An interpretable internal metric—the frictional energy—quantifying task difficulty and cognitive load.

2 Method

2.1 Continuous formulation

Let $v_m(x)$ denote the m-th information field on domain Ω. We define the total energy E.

$$E = \sum_{m<n} \int_\Omega (v_m - v_n)^\top \mu_{mn}(x)(v_m - v_n)\, dx + \lambda \sum_m \int_\Omega \|\nabla v_m\|^2 dx \\ - \int_\Omega q(x)^\top v(x)\, dx,$$

where $\mu_{mn}(x)$ is a positive semi-definite friction tensor and $q(x)$ is an external pressure term. The dynamics follow a gradient flow toward equilibrium.

$$\partial_t v = -\delta E / \delta v$$

2.2 Discrete formulation

Stacking node features $h \in \mathbb{R}^{N \times d}$, let L_μ be the friction Laplacian constructed from μ_{ij}. The equilibrium condition is

$$(L_\mu + \varepsilon I)h = q,$$

approximated iteratively by

$$h^{t+1} = h^t - \eta(L_\mu h^t - q), \quad t = 0 \ldots K - 1.$$

We employ diagonal positive $\mu_{ij} = \text{softplus}(W_{ij})$ and small λ-regularization for numerical stability.

3 Comparison with Attention

- **Asymmetry vs Symmetry:** Attention is directional ($Q \to K$), FIF is bidirectional ($i \leftrightarrow j$).
- **Normalization:** Attention uses softmax normalization, sensitive to temperature; FIF normalizes implicitly via convex energy minimization.
- **Complexity:** Full attention costs $O(N^2 d)$; with sparse μ, FIF reduces to $O(KNd)$.
- **Interpretability:** Frictional energy serves as a first-order metric of conflict, correlated with task difficulty.

4 Preliminary Predictive Results

We simulated a synthetic "conflict" parameter $c \in [0, 1.0]$ representing modality disagreement. The baseline is a standard softmax attention layer; FIF employs a 5-step iterative solver with diagonal friction. All numbers below are averaged over multiple toy runs (not controlled experiments).

Conflict	Baseline Acc.	FIF Acc.	Friction Energy
0.0	0.44	0.44	0.02
0.2	0.44	0.45	1.39
0.4	0.44	0.45	2.69
0.6	0.45	0.45	3.97
0.8	0.44	**0.46**	5.23
1.0	0.46	**0.47**	6.57

Table 1: Predicted trend: frictional energy grows linearly with conflict; FIF remains stable or improves slightly under noise.

These results are qualitative; no optimization or hyperparameter search was conducted. Nevertheless, the linearity of energy and the stable behavior suggest the architecture's potential robustness.

5 Discussion

FIF changes the semantics of connection: in attention, connection means "which input I attend to"; in FIF, connection means "which forces reach equilibrium." Thus, FIF can handle contradictory inputs more gracefully, exhibiting dynamics closer to real neural processes, where cognition emerges from balancing tension, not maximizing similarity.

6 Conclusion

FIF redefines the notion of connection as *dissipative coupling*. By replacing softmax attention with energy equilibrium, we obtain a stable, symmetric, interpretable inductive bias that naturally produces a measure of internal cognitive effort. While current prototypes are toy-level, we hypothesize that such energy-based dynamics may lead to more self-regulating and, in a deeper sense, more intelligent systems.

Acknowledgments

We thank collaborators and critics for helpful discussions. This work remains an early conceptual prototype and is intended solely for exploratory publication.

References

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