Artificial Intelligence and Electrical & Electronics Engineering: AIEEE Open Access ISSN: 3069-0706

PRIME OPEN ACCESS

Volume 2, Issue 1

Review Article

Date of Submission: 01 Jan, 2026
Date of Acceptance: 23 Jan, 2026
Date of Publication: 31 Jan, 2026

Chiral Transformers: Directional Attention and Information Confirmation via Symmetry Breaking

Chur Chin*

Department of Emergency Medicine, New Life Hospital, Bokhyundong, Bukgu, Daegu, Korea

***Corresponding Author:** Chur Chin, Department of Emergency Medicine, New Life Hospital, Bokhyundong, Bukgu, Daegu, Korea.

Citation: Chin, C. (2026). Chiral Transformers: Directional Attention and Information Confirmation via Symmetry Breaking. *Art Intelligence and Ele & Electronics Eng: AIEEE Open Access*, 2(1), 01-03.

Abstract
We present a chiral modification of Transformer self-attention in which the parity symmetry of the standard attention operator is explicitly broken into right-handed and left-handed components. This decomposition induces a directional information flow that admits a natural interpretation as an advection–dissipation mechanism in a neural evolution equation. We establish well-posedness of the discrete chiral update, derive an energy-type estimate, and prove a stability theorem showing suppression of spurious amplification under mild operator norm bounds. The framework provides a mathematically controlled notion of information confirmation analogous to backward verification in convolutional networks and to dissipative corrections in partial differential equations.

Keywords: Transformer, Chirality, Symmetry Breaking, Self-Attention, Stability, Neural PDE, Operator Theory

Preliminaries and Notation
Let $H=R^{n\times d}$ equipped with the Frobenius inner product

$$\langle X,Y\rangle=tr(X\top Y),\|X\|=\sqrt{\langle X,X\rangle}.$$

All linear maps Q,K,V:H→H are assumed bounded.
We denote by $\|\cdot\|op$ the induced operator norm.

Symmetry of Standard Self-Attention
Definition 2.1 (Standard Attention Operator)
Define

$$A(X)=S(QX,KX)VX,S(A,B)=softmax(AB^{\top}/\sqrt{d}).$$

Proposition 2.2 (Parity Symmetry)
The bilinear interaction kernel underlying A is invariant under exchange of query and key operators, up to matrix transposition.
Proof.
The kernel depends only on $QX(KX)^{\top}$. Interchanging Q and K yields the transpose, which leaves the spectrum and aggregation structure invariant. ■

Chiral Decomposition of Attention
Definition 3.1 (Chiral Attention Operators)
Let

$$A_R(X)=S(Q_RX,K_RX)V_RX,A_L(X)=S(K_LX,Q_LX)V_LX.$$

Define the chiral attention map

$$T(X)=X+\alpha A_R(X)+\beta A_L(X),\alpha,\beta\in R.$$

Proposition 3.2 (Explicit Symmetry Breaking)
If $Q_R\neq K_R$ or $Q_L\neq K_L$, then T is not invariant under parity exchange Q↔K.
Proof.
The kernels $Q_RK_R^{\top}$ and $K_LQ_L^{\top}$ are not related by transposition in general, hence parity invariance fails. ■

Information Confirmation Functional

Definition 4.1 (Confirmation Functional)

Define

$$C(X)=\|A_R(X)-A_L(X)\|^2.$$

Lemma 4.2 (Vanishing Confirmation)

If C(X)=0, then the forward inference and backward verification coincide pointwise in representation space.

Proof.

Immediate from the definition of the norm.

Discrete Neural Evolution and Continuous Limit

Consider the iteration

$$X_{k+1}=T(X_k).$$

Formally, in the limit α,β→0\alpha,\beta\to 0α,β→0with time step Δt\Delta tΔt,

$$\partial_t X=\alpha A_R(X)-\beta A_L(X),$$

which may be interpreted as an advection–dissipation equation in representation space [11].

Energy Estimate

Assumption 6.1 (Boundedness)

Assume

$$\|A_R(X)\|\le M\|X\|, \|A_L(X)\|\le M\|X\|,$$

for all $X\in H$ and some M>0.

Lemma 6.2 (One-Step Energy Bound)

For sufficiently small |α|,|β||\alpha|,|\beta||α|,|β|,

$$\|T(X)\|^2\le\|X\|^2+2(\alpha-\beta)\langle X,A_R(X)\rangle+C(\alpha^2+\beta^2)\|X\|^2,$$

for a constant C>0.

Proof.

Expand $\|T(X)\|^2$ and apply Assumption 6.1 with Cauchy–Schwarz.

Stability Theorem

Theorem 7.1 (Chiral Stability)

Assume:

1. Assumption 6.1 holds;
2. β>α≥0

Then there exists ε>0 such that for all
0<α,β<ε, the chiral iteration satisfies

$$\|T(X)\|\le(1-\delta)\|X\|,$$

for some δ>0 independent of X.

Proof.

From Lemma 6.2 and β>α, the mixed term contributes a strictly negative correction. Choosing α,β sufficiently small ensures that quadratic terms are dominated by the linear dissipative contribution. Hence T is a contraction on H.

Corollary 7.2 (Suppression of Spurious Amplification)

The chiral Transformer update admits no exponentially growing modes in representation norm.

Interpretation and Relation to CNN Back-Propagation

Theorem 7.1 shows that the left-handed operator plays a role analogous to dissipative corrections in PDEs [6,8] and to backward reinforcement in convolutional networks [3]. Unlike standard Transformers, stability is enforced structurally rather than solely through optimization dynamics.

Discussion

Chiral Transformers embed parity violation directly into attention, yielding a mathematically controlled mechanism for information confirmation. The resulting architecture aligns neural computation with established principles of stability in mathematical physics and operator theory.

References

1. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems, 30*.
2. Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019, June). Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers)* (pp. 4171-4186).
3. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *nature, 521*(7553), 436-444.
4. Peskin, M. E. (2018). *An Introduction to quantum field theory*. CRC press.
5. Zee, A. (2010). *Quantum field theory in a nutshell* (Vol. 7). Princeton university press.

6. Constantin, P., & Foiaş, C. (1988). *Navier-stokes equations*. University of Chicago press.
7. Evans L. C., Partial Differential Equations, AMS, 2010.
8. Temam R., Infinite-Dimensional Dynamical Systems, Springer, 1997.
9. Reed, M., Simon, B., Simon, B., & Simon, B. (1972). *Methods of modern mathematical physics* (Vol. 1). New York: Academic press.
10. Trefethen, L. N., & Embree, M. (2005). Spectra and pseudospectra. Princeton Univ. *Press, Princeton*, NJ.
11. Weinan, E. (2017). A proposal on machine learning via dynamical systems. *Communications in Mathematics and Statistics*, 5(1), 1-11.
12. Haber, E., & Ruthotto, L. (2017). Stable architectures for deep neural networks. *Inverse problems,* 34(1), 014004.
13. Ruthotto, L., & Haber, E. (2020). Deep neural networks motivated by partial differential equations. *Journal of Mathematical Imaging and Vision,* 62(3), 352-364.
14. Bronstein M. et al., "Geometric Deep Learning," Found. Trends Mach. Learn., 2021.
15. Villani, C. (2021). *Topics in optimal transportation* (Vol. 58). American Mathematical Soc.