Phase-Aware Training of a Dynamical Photonic Network

A Stable Real–Imaginary Parameterization for Learning Interference-Based Computation

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Abstract

Photonic and wave-based computing architectures offer the promise of massively parallel computation via interference and phase dynamics. However, training such systems with gradient-based methods remains challenging due to phase discontinuities, unstable complex-valued gradients, and mismatches between simulation and learning dynamics.

In this work, we present a phase-aware training method for a dynamical photonic network that explicitly parameterizes connectivity in real–imaginary form, avoiding angle-based representations. We demonstrate stable end-to-end training of a recurrent, interference-driven photonic substrate on the MNIST classification task, achieving ∼95% test accuracy without convolutional structure or digital depth.

Our results show that (i) phase degrees of freedom materially increase learnable capacity, (ii) dynamical rollouts must be matched between training and evaluation, and (iii) modest classification performance is sufficient to validate the feasibility of learning interference-based computation. This work establishes a practical bridge between photonic simulation and gradient-based optimization.

1 Introduction

Wave-based computing systems—optical, photonic, and analog—naturally implement linear superposition, interference, and parallel signal propagation. These properties suggest an alternative computational substrate to digital neural networks, potentially offering advantages in throughput, energy efficiency, and physical realizability.

Despite this promise, training photonic systems remains difficult. Unlike real-valued neural networks, photonic systems evolve in complex-valued state spaces where phase is essential to computation. Naïve representations using magnitude and phase often introduce discontinuities and unstable gradients, while direct complex-valued automatic differentiation can be numerically fragile.

This work addresses a practical question:

> *Can a recurrent, interference-based photonic system be trained stably using gradient descent, while preserving phase as a meaningful computational resource?*

We answer this in the affirmative by introducing a real–imaginary parameterization of photonic connectivity and demonstrating stable training of a dynamical photonic network.

2 Related Work

Photonic neural networks have been explored in multiple contexts, including optical matrix multiplication, reservoir computing, and diffractive optical elements. Prior work has demonstrated inference using fixed optical components and training using external optimization loops.

Complex-valued neural networks have also been studied in machine learning, but practical adoption remains limited due to instability in phase-based gradients and lack of robust tooling.

Our approach differs in two key ways:

- We train a *recurrent, dynamical* photonic system rather than a single-pass optical transform.
- We avoid polar (magnitude–phase) representations entirely during training.

3 Photonic Network Model

3.1 State Representation

The photonic network state is represented as a complex-valued field:

$$\mathbf{F}(t) \in \mathbb{C}^{B\times S\times \Lambda\times M},$$

where B is batch size, S is the number of switches, Λ is the number of wavelength channels, and M is the number of spatial modes.

Each timestep represents a physical evolution of the network, including propagation, interference, dispersion, and nonlinear saturation.

3.2 Connectivity and Phase

Rather than parameterizing connections as complex magnitudes and phases, we represent each connection as:

$$W_{ij} = W_{ij}^{(R)} + iW_{ij}^{(I)},$$

where $W_{ij}^{(R)}$ and $W_{ij}^{(I)}$ are independent real-valued parameters.

This avoids discontinuities at zero magnitude and preserves smooth gradients throughout training.

3.3 Nonlinearity

We apply a phase-preserving nonlinear activation of the form:

$$\mathbf{F}_{\text{out}} = \mathbf{F}_{\text{in}} \cdot \frac{f(|\mathbf{F}_{\text{in}}|)}{|\mathbf{F}_{\text{in}}| + \epsilon},$$

where $f(\cdot)$ is a bounded saturation function. This rescales magnitude while preserving phase.

4 Training Method

4.1 Dynamical Rollout

Inputs are injected into a subset of switches for a fixed number of timesteps, after which the system evolves freely. Outputs are read as integrated energy at designated output switches:

$$E = \sum_{\lambda,m} |\mathbf{F}_{\text{out}}|^2.$$

Crucially, we found that *training and evaluation must use identical rollout dynamics*. Mismatched rollouts can drive the system into different attractors, severely degrading performance.

4.2 Optimization

The network is trained end-to-end using Adam with gradient clipping. A very small L_2 regularization term is optionally applied to connectivity weights to stabilize training.

5 Experimental Setup

5.1 Task

We evaluate the system on the MNIST handwritten digit classification task. Images are encoded as spatial patches and injected into a "visual" region of the photonic network.

No convolutional layers, pooling, or digital feature extractors are used.

5.2 Architecture

The network consists of ∼200 switches organized into hierarchical regions inspired by visual processing stages (V1, V2, V4, IT, OUT), with sparse recurrent connectivity.

5.3 Baselines

Our goal is not state-of-the-art accuracy, but validation of learning dynamics. For reference, small convolutional networks routinely exceed 99% accuracy on MNIST.

6 Results

The phase-aware photonic network achieves stable training and reaches peak test accuracy of approximately 94–95% on MNIST.

Training is reproducible across epochs, with test accuracy tracking training accuracy and no catastrophic collapse when rollout dynamics are matched.

Table 1: Representative MNIST Performance

Model	Test Accuracy	Notes
Photonic (phase-aware)	∼95%	This work
Small CNN	>99%	Digital baseline

7 Discussion

The achieved accuracy is intentionally modest. Its significance lies not in absolute performance, but in demonstrating that:

- Phase can be trained stably using gradient descent.
- Interference-based dynamics meaningfully contribute to computation.
- Dynamical photonic systems can generalize beyond training data.

These results validate phase-aware training as a viable pathway toward photonic learning systems.

8 Limitations and Future Work

This work is limited to simulation and a single benchmark task. Future directions include:

- Direct comparison with magnitude-only ablations.
- Scaling to larger datasets and continuous signals.
- Hardware-informed constraints and energy modeling.
- Physical photonic implementations.

9 Conclusion

We have demonstrated a practical method for training a dynamical photonic network using a real–imaginary parameterization that preserves phase while enabling stable optimization. The results establish a functional bridge between photonic simulation and gradient-based learning and motivate further exploration of interference-driven computation.

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