

# Frequency-Selective Optical Perceptrons with Angle-Tunable Weights for Continuous Online Learning

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## Abstract

We propose a novel optical neural network architecture based on frequency-selective surfaces with angle-tunable transmission characteristics. Unlike existing optical neural networks that require fixed weights after fabrication or complex interferometric setups, our approach encodes learnable weights as the physical angles of frequency-selective optical elements. The transmission coefficient of each element varies smoothly with angle, providing a continuous weight space in  $[-1, +1]$  through a phase-mapping transformation. We validate this architecture through numerical simulation, demonstrating successful learning of all basic logic gates (AND, OR, NAND, NOR) with single-layer networks and XOR with multi-layer networks, confirming universal approximation capability. The key advantages of this approach include: (1) non-volatile weight storage through physical angles, (2) potential for continuous online learning via mechanical or electro-optic angle adjustment, and (3) forward inference at the speed of light. We present the mathematical framework, simulation results, and discuss candidate materials and implementation strategies for bulk tabletop prototypes. This work is released as an open concept to encourage hardware implementation by the photonics community.

**Keywords:** optical neural networks, photonic computing, neuromorphic hardware, frequency-selective surfaces, online learning

## 1 Introduction

The computational demands of modern deep learning have grown exponentially, with model sizes doubling approximately every 4-6 months [1]. This growth is pushing the limits of conventional electronic hardware, motivating exploration of alternative computing paradigms. Optical neural networks (ONNs) have emerged as a promising direction, offering potential advantages in speed (computations at the speed of light), energy efficiency (passive optical propagation requires no power), and parallelism (wavelength and spatial multiplexing) [2].

Several approaches to optical neural networks have been demonstrated:

- **Mach-Zehnder Interferometer (MZI) meshes:** Networks of programmable interferometers implement matrix-vector multiplication through phase shifts [3, 4]. Companies like Lightmatter and Lightelligence are commercializing this approach.
- **Diffractive Deep Neural Networks (D<sup>2</sup>NN):** 3D-printed or lithographically fabricated diffractive layers process information through optical diffraction [5]. These achieve remarkable inference speed but have *fixed weights* after fabrication.

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- **Spatial Light Modulator (SLM) systems:** Programmable liquid crystal arrays enable reconfigurable optical processing [6], but require complex control electronics and have limited update rates.

A key limitation of current approaches is the separation between training and inference. Most optical neural networks are trained in software on conventional computers, with the learned weights then transferred to optical hardware. True *online learning*—where the optical system itself adapts its weights during operation—remains challenging.

## 1.1 Our Contribution

We propose a fundamentally different architecture: **frequency-selective optical perceptrons with angle-tunable weights**. The key insight is that:

1. Frequency-selective optical elements (dichroic filters, Fabry-Pérot etalons, photonic crystals) exhibit transmission characteristics that depend on the angle of incidence.
2. This angle-dependent transmission can be mapped to a continuous weight value through a simple transformation.
3. The angle is a *physical, non-volatile* parameter that can be adjusted for learning and retained without power.

This architecture enables, in principle, continuous online learning in optical hardware—the optical system can adjust its own weights through mechanical (motorized rotation stages) or electro-optic (liquid crystal, MEMS) angle control.

We validate this concept through numerical simulation, demonstrating that the architecture can learn all basic logic gates and solve the XOR problem (a canonical test of nonlinear capability). We release the simulation code openly and discuss implementation pathways using commercially available optical components.

## 2 Proposed Architecture

### 2.1 Single Optical Perceptron

A conventional artificial neuron computes:

$$y = \sigma \left( \sum_{i=1}^n w_i x_i + b \right) \quad (1)$$

where  $x_i$  are inputs,  $w_i$  are weights,  $b$  is a bias, and  $\sigma$  is a nonlinear activation function.

In our optical implementation, we propose encoding each weight  $w_i$  as the *angle*  $\theta_i$  of a frequency-selective surface. The mapping from angle to weight proceeds through two stages:

**Stage 1: Angle to Transmission.** The transmission coefficient  $T$  of a frequency-selective surface at a fixed input frequency varies with angle according to a sigmoid-like curve:

$$T(\theta) = \frac{1}{1 + e^{-k\theta}} \quad (2)$$

where  $k$  is a sharpness parameter determined by the material properties. This gives  $T \in [0, 1]$ .

**Stage 2: Transmission to Signed Weight.** To obtain weights in the range  $[-1, +1]$ , we apply a linear transformation:

$$w = 2T - 1 = \frac{2}{1 + e^{-k\theta}} - 1 \quad (3)$$

This mapping has a natural physical interpretation in terms of optical phase:

- $T \approx 0 \Rightarrow w \approx -1$ : Destructive interference or phase-shifted transmission
- $T \approx 0.5 \Rightarrow w \approx 0$ : Partial transmission
- $T \approx 1 \Rightarrow w \approx +1$ : Full transmission

## 2.2 Forward Pass

The forward pass of an optical perceptron with  $n$  inputs proceeds as follows:

1. **Input encoding:** Each input  $x_i \in [0, 1]$  is encoded as the amplitude (intensity) of light in channel  $i$ . Channels may be separated spatially or by wavelength.
2. **Weight application:** Each channel passes through its corresponding frequency-selective surface at angle  $\theta_i$ . The transmitted intensity is  $T(\theta_i) \cdot x_i$ .
3. **Summation:** A detector collects light from all channels. The total signal is:

$$z = \sum_{i=1}^n w(\theta_i) \cdot x_i + b \quad (4)$$

where the weight mapping and summation may be performed optically or with minimal electronics.

4. **Activation:** A nonlinear activation is applied:

$$y = \sigma(z) = \frac{1}{1 + e^{-\alpha z}} \quad (5)$$

This can be implemented electronically (threshold comparator) or optically (saturable absorber).

## 2.3 Multi-Layer Networks

For problems requiring nonlinear decision boundaries (e.g., XOR), we cascade multiple layers of optical perceptrons. The output of layer  $\ell$  becomes the input to layer  $\ell + 1$ :

$$\mathbf{y}^{(\ell+1)} = \sigma \left( \mathbf{W}^{(\ell)} \mathbf{y}^{(\ell)} + \mathbf{b}^{(\ell)} \right) \quad (6)$$

where each element of  $\mathbf{W}^{(\ell)}$  is encoded as an angle in the corresponding optical element.

## 2.4 Training via Angle Adjustment

Training proceeds by gradient descent on the angles. For a loss function  $\mathcal{L}$ , we update:

$$\theta_i \leftarrow \theta_i - \eta \frac{\partial \mathcal{L}}{\partial \theta_i} \quad (7)$$

The gradient  $\frac{\partial \mathcal{L}}{\partial \theta_i}$  can be estimated:

1. **Numerically:** Perturb  $\theta_i$  by  $\pm \epsilon$ , measure output change, compute finite difference.
2. **Analytically:** Backpropagate through the known transmission function  $T(\theta)$ .

In a physical implementation, numerical gradient estimation corresponds to slightly tilting each optical element and measuring the resulting change in output—a physically realizable operation.

### 3 Simulation Framework

We implemented the proposed architecture in Python to validate its computational capability. The simulation models:

- Angle-to-transmission mapping via sigmoid function
- Transmission-to-weight mapping via  $w = 2T - 1$
- Multi-layer network topology
- Gradient descent training with numerical gradient estimation

#### 3.1 Single Perceptron Implementation

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**Algorithm 1** Optical Perceptron Forward Pass

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**Require:** Input vector  $\mathbf{x}$ , angles  $\boldsymbol{\theta}$ , bias  $b$ , sharpness  $k$

**Ensure:** Output  $y$

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1: for  $i = 1$  to  $n$  do
2:    $T_i \leftarrow \frac{1}{1+e^{-k\theta_i}}$                                  $\triangleright$  Transmission
3:    $w_i \leftarrow 2T_i - 1$                                  $\triangleright$  Signed weight
4: end for
5:  $z \leftarrow \sum_{i=1}^n w_i x_i + b$                        $\triangleright$  Weighted sum
6:  $y \leftarrow \frac{1}{1+e^{-\alpha z}}$                        $\triangleright$  Activation
7: return  $y$ 

```
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#### 3.2 Training Algorithm

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**Algorithm 2** Training via Numerical Gradient Descent

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**Require:** Training data  $\{(\mathbf{x}_j, t_j)\}$ , learning rate  $\eta$ , perturbation  $\epsilon$

- ```

1: for each epoch do
2:   for each training sample  $(\mathbf{x}, t)$  do
3:     for each angle  $\theta_i$  do
4:        $\theta_i \leftarrow \theta_i + \epsilon$ 
5:        $\mathcal{L}_+ \leftarrow (y - t)^2$                                  $\triangleright$  MSE loss
6:        $\theta_i \leftarrow \theta_i - 2\epsilon$ 
7:        $\mathcal{L}_- \leftarrow (y - t)^2$ 
8:        $\theta_i \leftarrow \theta_i + \epsilon$                                  $\triangleright$  Restore
9:        $g_i \leftarrow \frac{\mathcal{L}_+ - \mathcal{L}_-}{2\epsilon}$                    $\triangleright$  Gradient estimate
10:       $\theta_i \leftarrow \theta_i - \eta \cdot g_i$                           $\triangleright$  Update
11:    end for
12:    Update bias  $b$  similarly
13:  end for
14: end for

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### 4 Results

#### 4.1 Logic Gate Learning

We tested single-layer optical perceptrons on the four basic two-input logic gates. Each network has 2 inputs and 1 output. Training used mean squared error loss with learning rate  $\eta = 0.5$  for 800-1500 epochs.

Table 1: Logic Gate Learning Results

Gate	Accuracy	Learned $w_1$	Learned $w_2$	Learned $b$
AND	100%	+0.997	+0.996	-1.493
OR	100%	+0.996	+0.997	-0.411
NAND	100%	-0.997	-0.996	+1.493
NOR	100%	-0.996	-0.997	+0.411

All four gates were learned perfectly. The learned weights are interpretable:

- AND/OR: Positive weights, bias determines threshold
- NAND/NOR: Negative weights (inverted logic)

## 4.2 XOR Learning (Nonlinear Problem)

XOR is not linearly separable and requires a multi-layer network. We used a 2-4-1 architecture (2 inputs, 4 hidden neurons, 1 output).

Table 2: XOR Learning Results

Input	Target	Output	Correct
(0, 0)	0	0.063	✓
(0, 1)	1	0.743	✓
(1, 0)	1	0.738	✓
(1, 1)	0	0.138	✓

The network achieves 100% accuracy on XOR, confirming that the architecture supports nonlinear computation through multi-layer composition. This demonstrates **universal approximation capability**—the architecture can, in principle, learn any Boolean function.

## 4.3 Convergence Analysis

Training converged reliably across multiple random initializations:

- Single-layer gates: Converged within 500-1000 epochs
- XOR: Converged within 1000-2000 epochs (depending on initialization)
- Loss decreased monotonically in successful runs

Some initializations for XOR led to local minima, a known challenge for gradient-based training of multi-layer networks. This was mitigated by trying multiple random seeds.

## 5 Discussion

### 5.1 Advantages of the Proposed Architecture

**Non-volatile weight storage.** Unlike electronic neural networks requiring continuous power to maintain weights in memory, our optical weights are stored as physical angles. A motorized mount, once positioned, retains its angle indefinitely.

**Continuous online learning potential.** The architecture naturally supports online learning: detect error, adjust angles, repeat. This is difficult to achieve in fixed-mask approaches like D<sup>2</sup>NN.

**Speed of light inference.** Forward propagation occurs at optical speeds. Once angles are set, inference requires only photon transit time through the optical system.

**Energy efficiency.** Passive optical elements require no power for inference. Energy is only consumed during weight updates (angle adjustment).

## 5.2 Implementation Pathways

We identify several candidate technologies for physical implementation:

Table 3: Candidate Technologies for Physical Implementation

Technology	Angle Adjustment	Approx. Cost
Dichroic filters + rotation stages	Motorized mounts	\$2,000-5,000
Acousto-optic tunable filters	RF frequency control	\$10,000-20,000
Liquid crystal variable retarders	Electronic control	\$500-2,000
MEMS mirror arrays	Electrostatic actuation	Research-grade

A minimal proof-of-concept could be constructed with off-the-shelf dichroic filters (e.g., from Thorlabs or Edmund Optics) mounted on motorized rotation stages, a broadband light source, and photodetectors.

## 5.3 Open Challenges

**Multi-input optical summation.** Our architecture requires summing weighted contributions from multiple inputs. Options include spatial superposition (all beams on one detector), wavelength multiplexing, or electronic summation after detection.

**Layer-to-layer coupling.** In multi-layer networks, the output of one layer must become the input to the next. This may require optical-electronic-optical conversion or clever free-space propagation design.

**Activation function implementation.** We assume sigmoid activation, which can be implemented electronically. All-optical nonlinearity (saturable absorbers, two-photon absorption) remains an active research area.

**Scaling.** Our simulations validated small networks (2-4 neurons). Scaling to larger networks requires addressing crosstalk, alignment, and control complexity.

## 5.4 Relation to Existing Work

Our approach is complementary to existing optical neural network research:

- Unlike MZI-based systems [3], we use frequency-selective transmission rather than phase interference.
- Unlike D<sup>2</sup>NN [5], our weights are continuously tunable after fabrication.
- Unlike SLM-based systems, our weights have a direct physical interpretation (angle) and potential for simpler implementation.

## 6 Conclusion

We have proposed and validated a novel optical neural network architecture based on frequency-selective surfaces with angle-tunable weights. Key contributions include:

1. A physically-motivated mapping from optical element angle to neural network weight

2. Simulation demonstrating successful learning of all basic logic gates
3. Demonstration of nonlinear capability through XOR learning with multi-layer networks
4. Identification of implementation pathways using commercial optical components

We release this work openly to encourage hardware implementation by researchers with optical/photonics expertise. The simulation code is available at: <https://github.com/yoctotta-software/optical-perceptron>

## 6.1 Call for Collaboration

The authors lack hardware fabrication capabilities but believe this concept merits physical validation. We invite collaboration from:

- Photonics researchers with optical bench access
- Companies developing optical computing hardware
- Research groups working on neuromorphic systems

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## Code Availability

Simulation code is available at: <https://github.com/yoctotta-software/optical-perceptron>

## Competing Interests

The author declares no competing interests.

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## A Simulation Code

The core simulation is implemented in approximately 150 lines of Python using only NumPy. Key components:

```
class OpticalPerceptron:
    def __init__(self, n_inputs):
        self.angles = np.random.randn(n_inputs) * 0.3
        self.bias = 0.0

    def weight(self, i):
        T = 1.0 / (1.0 + np.exp(-2.0 * self.angles[i]))
        return 2.0 * T - 1.0 # Map [0,1] -> [-1,+1]

    def forward(self, x):
        z = sum(self.weight(i) * x[i] for i in range(self.n))
        return 1.0 / (1.0 + np.exp(-4.0 * (z + self.bias)))
```

Full code available in the GitHub repository.