Supplementary Materials for

Reconfigurable Optical Synaptic Weighting Engine Using a Liquid Crystal-Based Multimode Interference Coupler

Supplementary Note 1 : Non-Negative Weight Implementation

The current implementation inherently supports non-negative weighting due to the nature of optical power transmission, which cannot represent negative values directly. However, enabling signed weights is essential for realizing more expressive and general-purpose neural network models. We have expanded the discussion to outline feasible strategies for achieving signed weight representations:

1. Balanced Photodetector Schemes:

One practical method to enable signed weights involves the use of balanced photodetectors. By routing the outputs of two optical channels—one representing a positive contribution and the other a negative counterpart—into a differential photodetector, the effective output can represent a signed weight. This approach has been demonstrated in other photonic neuromorphic systems [1] and is compatible with our architecture by assigning complementary optical paths controlled via tuning pads.

2. Differential Detection Architectures:

Alternatively, a differential detection setup can be realized using a pair of MMIs operating in parallel, with each MMI encoding either positive or negative weight values. The difference in their optical outputs can then be electronically processed to emulate signed operations. While this increases the device footprint and complexity slightly, it offers a scalable path toward implementing full-range weight matrices.

3. Coherent Interference Schemes:

In future extensions, we envision leveraging coherent optical inputs in combination with calibrated phase control to support signed or even complex-valued weights. While interference naturally governs MMI behavior, precise control over the input phase profile and internal modulation can be used to tailor the interference outcomes, enabling encoding of both weight polarity and magnitude. Balanced photodetector schemes may then be employed to extract differential signals, realizing signed weight operations.

Supplementary Note 2 : A comparative analysis of existing reconfigurable photonic hardware platforms

Table S1

A comparison of the proposed LC-tuned MMI neural networks with previously reported existing reconfigurable neural networks

Platform	Reconfigurable Element	Inference Accuracy	Reconfiguration Power	Speed / Response Time	Programmability / Endurance
Microring Resonators [2]	Thermo-optic tuning	~ 93% (Iris)	~ 20 mW	~ 1-100 µs	High
PCM-based [3, 4]	Phase-change material ($Ge_2Sb_2Te_5$)	~ 95% (MNIST)	~ 5.33 mW † (Non-volatile)	ns–µs (phase transition)	Limited (finite endurance)
MZI Meshes (e.g., Reck/Clements) [5]	Thermo-optic phase shifters	~92.5% (vowel classification)	~25 mW	~1 µs	High but sensitive to drift
Current-controlled attenuators [6]	Forward biasing the PIN junction	~ 89.8 % (four-class handwritten letters)	~ 80 mW †	~46 ps	High
Electro-absorption modulator-based Photonics [7, 8]	SiGe EAM	~95.91% (MNIST)	~ 0.25 mW	~ 20 ps	High (fast reprogramming)
Hybrid MOS Optical Phase Shifter [1, 9]	Transparent Conducting Oxides	Emerging (data not available)	~1 nW	~1 ns (electro-optic)	High (fast, CMOS-compatible)
This Work (LC-MMI) (This work)	Liquid crystal (LC) tuned MMI	86.67% (Iris)	~ nW	~ms (LC switching)	High (electrical tuning)

† Estimated average power

The LC-MMI architecture proposed in this work demonstrates competitive accuracy (86.67% on the Iris dataset) and stands out for its low power consumption (~ nW) and high programmability via electrically controlled liquid crystals. Although its response time (~ ms) is slower compared to electro-optic or PCM-based platforms, it is sufficient for inference-dominant or low-update-rate applications.

Supplementary Note 3 : Description of variables used in the equations presented in Figure 1

Table S2

Symbol	Definition
$\Psi(x, z)$	Optical field distribution in the multimode interference (MMI) region as a function of position (x, z)
M	Number of supported optical modes in the MMI region.
c_i	Amplitude coefficient of the i-th mode
$\Psi_i(x)$	Transverse mode profile of the i-th mode
βi	Propagation constant of the i-th mode
$\beta 0$	Propagation constant of the fundamental mode
z	Longitudinal propagation distance
Npads	Number of liquid crystal (LC) tuning pads used for phase control
$\alpha_{ik}(Vk)$	Number of liquid crystal (LC) tuning pads used for phase control
$W_{ij}(V)$	Synaptic weight representing the optical transfer function between input i and output j, controlled by voltage V
C_{im}	Optical Mode coupling coefficient between input mode i and mode m
C^*_{jm}	Complex conjugate of the mode coupling coefficient for output mode j
βm	Propagation constant of mode m
L	Physical length of the multimode region
$\phi_{ij}(V)$	Phase shift induced between input i and output j by voltage V
X_i	Input vector (optical signals injected into waveguides)
Y_i	output vector (resulting optical signals)

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