Towards Area-Efficient Optical Neural Networks: An FFT-Based Architecture

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AI Acceleration and Challenges

- ML models and dataset keep increasing -> more computation demands
  - Low latency
  - Low power
  - High bandwidth

- Moore’s law is challenging to provide higher-performance computations
AI Acceleration and Challenges

- Using light to continue Moore’s Law
- Promising technology for next-generation AI accelerator

[Shen+, Nature Photonics 2017]
Optical Neural Networks (ONN)

- Emergence of neuromorphic platforms for AI acceleration
- Optical neural networks (ONNs)
  - Ultra-fast execution speed (light in and light out)
  - >100 GHz photo-detection rate
  - Near-zero energy consumption if configured
- Unsatisfactory hardware area cost
  - Mach-Zehnder Interferometers (MZI) are relatively large
  - Previous architecture costs lots of MZIs (area-inefficient)
  - Previous architecture is not compatible with network pruning

[Shen+, Nature Photonics 2017]
Previous MZI-based ONN Architecture

- Map weight matrix to MZI arrays
- Singular value decomposition
  - \( W = U \Sigma V^* \)
  - \( U \) and \( V^* \) are square unitary matrices
  - \( \Sigma \) is diagonal matrix
- Unitary group parametrization
  - \( U(n) = D \prod_{i=n}^{2} \prod_{j=1}^{i-1} R_{ij} \)
  - \( R_{ij} \) is planar rotation matrix
  - \( R_{ij} \) with phase \( \phi \) can be implemented by an MZI

\[
\begin{pmatrix}
  y_1 \\
  y_2 \\
\end{pmatrix} =
\begin{pmatrix}
  \cos \phi & \sin \phi \\
  -\sin \phi & \cos \phi \\
\end{pmatrix}
\begin{pmatrix}
  x_1 \\
  x_2 \\
\end{pmatrix}
\]
Previous MZI-based ONN Architecture

- Slimmed ONN architecture [ASPDAC’19 Zhao+]
- TUΣ decomposition
  - T is a sparse tree network for dimension matching
  - U is a square unitary matrix
  - Σ is diagonal matrix
- Use less # of MZIs
- Limits: only remove the smaller unitary

 Optical Inference Unit

Non-linearity

1st subtree

2nd subtree

3rd subtree

[ASPDAC’19 Zhao+]
Our Proposed FFT-ONN Architecture

- Efficient **circulant matrix multiplication** in Fourier domain
- 2.2~3.7X area reduction
- Without accuracy loss

**ST/CT**: Splitter/Combiner tree (Signal Fanout/Accumulation)
**OFFT/OIFFT**: Optical FFT/IFFT (Fourier Domain Transform)
**EM**: Element-wise multiplication (Weight Encoding in Fourier Domain)
Block-circulant Matrix Multiplication

- Not general matrix multiplication
- Block-circulant matrix: each $k \times k$ block is a circulant matrix

- Efficient algorithm in Fourier domain
- Comparable expressiveness to classical NNs. [ICLR’18 Li+]

$$y = Wx$$

$$y = \mathcal{F}^{-1}(\mathcal{F}(w) \odot \mathcal{F}(x))$$
Basic structure for 2-point FFT

1. 2 × 2 directional coupler
2. \(-\pi/2\) phase shifter

\[
\begin{pmatrix}
\text{out}_1 \\
\text{out}_2
\end{pmatrix} = \frac{1}{\sqrt{2}} \begin{pmatrix}
in_1 + in_2 \\
in_1 - in_2
\end{pmatrix}
= \begin{pmatrix}
1 & 0 \\
0 & -j
\end{pmatrix} \frac{1}{\sqrt{2}} \begin{pmatrix}
j & 1 \\
1 & j
\end{pmatrix} \begin{pmatrix}
1 & 0 \\
0 & -j
\end{pmatrix} \begin{pmatrix}
in_1 \\
in_2
\end{pmatrix}
\]
**Weight Encoding** \( \mathcal{F}(w) \odot \mathcal{F}(x) \)

- Multiplication in Fourier domain
  - Attenuator: magnitude modulation
  - Phase shifter: phase modulation
- Enable online/on-chip training
  - No complicated decomposition
  - Gradient backprop. friendly
- Splitter tree: fanout
- Combiner tree: accumulation
  - Fewer # of crossings: \( O(n) \)
Two-phase structured pruning
  › Group lasso regularization
  › Save 30% - 40% components
  › Without accuracy loss (<0.5%)

Masked Weight

Masked 4 x 4 block eliminates the corresponding hardware
Training Curve

- Same convergence speed as *w/o pruning*
- Negligible accuracy loss (<0.5%)
Pruning-compatibility Comparison

- Indirect and complicated
  \[ W = U \Sigma V^* \]
  \[ U(n) = D \prod_{i=n}^{2} \prod_{j=1}^{i-1} R_{i,j} \]
- Severe degradation

- Direct pruning
- No accuracy loss
Experimental Results

- 2.2~3.7X area cost reduction on various network configurations
- Similar accuracy (<0.5% diff)

\[ O(m^2 + n^2) \rightarrow O\left(\frac{mn}{k \log_2 k}\right) \]

![Diagram showing normalized area costs for different models with SVD and ΣU results compared to ours with and without pruning.](image)
Simulation Validation

- Lumerical INTERCONNECT tool
- Device-level numerical simulation
Simulation Validation

- Lumerical INTERCONNECT simulation (<1.2% maximum error)
  - 4 x 4 identity projection
    - (0,0,1,1)
    - (0,1,0,0)
    - (1,0,0,1)
    - (1,1,1,0)
  - 4 x 4 circulant matrix multiplication
    - (0,0,1,1)
    - (0,1,0,0)
    - (1,0,0,1)
    - (1,1,1,0)
FFT-based ONN Summary

♦ A new ONN architecture
  › Without using MZI
  › **2.2X ~ 3.7X** lower area cost
  › Near-zero accuracy degradation

♦ Fourier-domain ONN
  › Efficient neuromorphic computation using Fourier optics
  › Better compatibility to NN compression
  › Enable on-chip learning
Extension and Potential

- Beyond classical real matrix multiplication
  - Enhanced expressiveness w/ latent weights in the complex domain

- Beyond 1-D multi-layer perceptron
  - Extensible to 2-D frequency-domain optical convolution neural network

- Beyond inference acceleration
  - Efficient on-chip training / self-learning
Future Directions

Design for better robustness: FFT non-ideality; weight-encoding error

On-chip training framework for FFT-based ONN architecture

Chip tapeout and experimental testing
Thank you!
Q&A