Quantum Feature Extraction for THz Multi-Layer Imaging

Toshiaki Koike-Akino, Perry Wang
Mitsubishi Electric Research Laboratories (MERL), Cambridge, MA 02139, USA.

Genki Yamashita, Wataru Tsujita
Mitsubishi Electric Corporation Advanced Technology R&D Center, Hyogo 661-8661, Japan.

Makoto Nakajima
Institute of Laser Engineering, Osaka University, Osaka 565–0871, Japan.
Outline

• Trends of Artificial Intelligence (AI)
  – Deep Learning: Deep Neural Networks (DNN)
  – Post Deep Learning: Quantum Machine Learning (QML)

• THz Sensing for Non-Destructive Inspection
  – Inspection/Positioning
  – Challenges
  – DNN solutions
  – Hybrid QNN+DNN solutions
  – Experimental validation

• Summary
Artificial Intelligence (AI)

- K-means
- Gaussian mixture model (GMM)
- Principal component analysis (PCA)
- Independent component analysis (ICA)
- Logistic regression (LR)
- Support vector machine (SVM)
- Self-organizing map (SOM)
- Hidden Markov model (HMM)
- Artificial neural networks (ANN)
- Deep learning (DL)
- QML ...
DNN Architectures

- Residual Multi-Layer Perceptron (ResMLP)
- Residual Convolutional Neural Network (ResCNN)
- Bidirectional Long Short-Term Memory (BiLSTM)
- Transformer, U-net
- Implicit ODE, DEQ, CVX, ...

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AI Success in Media (Audio & Visual) Signal Processing

- Denoising, segmentation, classification, translation, dialog, recognition, decomposition, generation, super-resolution, ...
AI Surpassed Human-Level Performance

• For some applications like gaming
Deep Learning Crisis for Sustainable Growth

• Escalating power consumption of DNN training
  – [Strubell et al. Energy and policy considerations for deep learning in NLP. 2019]
  – 1-big DNN training with network architecture search (NAS) on GPUs requires 5-fold higher carbon emission of single car lifetime!

• New computing modality alternative to CPU/GPU/TPU is desired
  – Natural computing: Quantum computing, DNA computing, etc.

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<tr>
<th>Consumption</th>
<th>CO₂e (lbs)</th>
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<tr>
<td>Air travel, 1 passenger, NY↔SF</td>
<td>1984</td>
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<tr>
<td>Human life, avg, 1 year</td>
<td>11,023</td>
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<tr>
<td>American life, avg, 1 year</td>
<td>36,156</td>
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<tr>
<td>Car, avg incl. fuel, 1 lifetime</td>
<td>126,000</td>
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Training one model (GPU)

<table>
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<tr>
<th>Model</th>
<th>Hardware</th>
<th>Power (W)</th>
<th>Hours</th>
<th>kWh-PUE</th>
<th>CO₂e</th>
<th>Cloud compute cost</th>
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<tbody>
<tr>
<td>Transformer&lt;sub&gt;base&lt;/sub&gt;</td>
<td>P100x8</td>
<td>1415.78</td>
<td>12</td>
<td>27</td>
<td>26</td>
<td>$41–$140</td>
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<td>1515.43</td>
<td>84</td>
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<td>192</td>
<td>$289–$981</td>
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<td>ELMo</td>
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<td>336</td>
<td>275</td>
<td>262</td>
<td>$433–$1472</td>
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<td>V100x64</td>
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<td>79</td>
<td>1507</td>
<td>1438</td>
<td>$3751–$12,571</td>
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<tr>
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<td>TPUv2x16</td>
<td>—</td>
<td>96</td>
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<td>—</td>
<td>$2074–$6912</td>
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<td>656,347</td>
<td>626,155</td>
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<td>32,623</td>
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<tr>
<td>GPT-2</td>
<td>TPUv3x32</td>
<td>—</td>
<td>168</td>
<td>—</td>
<td>—</td>
<td>$12,902–$43,008</td>
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</table>

Table 1: Estimated CO₂ emissions from training common NLP models, compared to familiar consumption.¹

Table 3: Estimated cost of training a model in terms of CO₂ emissions (lbs) and cloud compute cost (USD).⁷ Power and carbon footprint are omitted for TPUs due to lack of public information on power draw for this hardware.
Quantum Computing

• Morgan Stanley: Quantum tech. can drive 4th industrial revolution
• Quantum processing units (QPU) vendors: IBM, Google, Microsoft, Honeywell, Intel, Nokia, AirBus, IONQ, rigetti, ...
• Quantum cloud services: IBMQ, Amazon Bracket, Microsoft Azure, ...
• Free libraries to evaluate quantum computing on realistic simulators or real devices
QPU development has been advancing rapidly to allow many qubits

- IBM released **127-qubit** QPUs in Nov. 2021
- IBM plans to release **1121-qubit** QPUs by 2023

**IBM QPU development roadmap (as of 2020)**

**IBM 127-qubit QPU (Nov. 2021)**
Quantum Supremacy

• Some reports claiming to have achieved **quantum supremacy**:
    ▪ 53-qubit QPU: 200 sec. for 10,000-year job required for classical computer
    ▪ Boson sampling: $10^{14}$ faster than classic computer

• Quantum advantage is still argued for general applications
Quantum Machine Learning (QML)

VQE: Variational Quantum Eigensolver, QAOA: Quantum Approximate Optimization Algorithm
QAE: Quantum AutoEncoder, QKSVM: Quantum Kernel Support Vector Machine, Q(W)GAN: Quantum (Wasserstein) Generative Adversarial Network,
QCNN: Quantum Convolutional Neural Network, QGNN: Quantum Graph Neural Net, QX: Quantum Experience, QCL: Quantum Circuit Learning, QKS: Quantum Kitchen Sink

Noisy intermediate-scale quantum (NISQ) algorithm

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Universal Approximation Theorem/Property (UAT/UAP)

- UAP for classical neural networks:
  - Single hidden neural networks can approximate arbitrary bounded continuous functions [Cybenko 1989]
  - Deep hidden neural networks can asymptotically approximate arbitrary functions [Zhou 2017]

- UAP still holds for quantum computing [Perez 2019]
  - Data re-uploading trick

Wider/deeper neurons can reduce approximation error

\[ h(\vec{x}) = \sum_{i=1}^{N} \alpha_i \varphi (\vec{w}_i \cdot \vec{x} + b_i) \]

\[ U(\vec{x}) = U_N(\vec{x})U_{N-1}(\vec{x}) \cdots U_1(\vec{x}) = \prod_{i=1}^{N} e^{i\vec{\omega}_i(\vec{x}) \cdot \vec{\phi}_i} \]

Wider neuron \( \rightarrow \) More quantum layers
Deeper layer \( \rightarrow \) More qubits
Differential Programming

• Quantum operation is differentiable:
  – Parameter shift rule [Mitarai/Schuld 2018] (exact gradient)

• Backpropagation through hybrid classical/quantum chips
  – Able to integrate (implicit) quantum layers into DNN models
  – e.g., Quanvolutional Neural Network [Henderson2019]

\[ \partial_{\mu} f(\mu) = c(f(\mu + s) - f(\mu - s)) \]
Quantum Neural Network (QNN)

- QML is a key major driver for **6G applications** [Nawaz et al. Access 2019]
- (Hyped) expectation of QNN advantage:
  - Fewer trainable parameters to support exponentially large quantum states in parallel
  - Parallel ensemble to prevent overfitting and underfitting
  - Low-power processing
Quantum Machine Learning (QML): Moore’s Law

- Number of articles on QML is doubling annually, just **6 years** behind of DNN
QML Meets Wi-Fi Sensing $\rightarrow$ THz Sensing

- **Indoor Monitoring:** [Koike-Akino, et al., "Quantum Transfer Learning for Wi-Fi Sensing", ICC 2022]
  - **Indoor Localization:** [Koike-Akino, et al., "Fingerprinting-Based Indoor Localization with Commercial MMWave WiFi: A Deep Learning Approach", Access 2020]
  - **Human Monitoring:** [Yu, et al., "Human Pose and Seat Occupancy Classification with Commercial MMWave WiFi", GLOBECOM 2020]
THz Sensing: Non-Destructive Inspection

- THz spectrum is located in between infrared (IR) and microwaves (MW)
- **Fine Resolution**: ultra-wideband spectrum for a wavelength of 300 µm at 1 THz
- THz wave **penetrates** many materials (advantages compared to IR) and exhibits better spatial resolution (compared to MW)
- Substances show **characteristic fingerprints** at THz spectrum due to collective molecular excitations
- THz wave is **non-ionizing**
THz Positioning: 1D Barcode

### Optical Encoders
- Linear
- Cylindrical

### Magnetic Encoders
- Linear
- Cylindrical
- Rotary

### Why THz encoder
- High-capacity 2D/3D positioning
- Robustness against dust, smoke & fire
- Resilient to light conditions
- Contactless (robust to vibration)

#### THz Polarizer + Metamaterial Absorber
(MERL, SPIE Photonics’18, IRMMW-THz’18, ’19’ 20)
Embedding Codes Into Polarization Angles Without Additional Reflections from Substrate

THz 1-D Barcode
- Polarization-based binary bit embedding

THz transceiver at 220-320 GHz
(collaboration with Prof. Ruonan Han (MIT))
THz Positioning: 2D QR-code

From THz barcode (Single Track) to THz QR code (Multiple Tracks)

1. THz-band spatial light modulator (SLM): OSU
2. Recovery algorithm of pseudo-random patterns: MERL (IRMMW-THz’18, ’20, ICASSP’18)

\[ y_n = a_n^T x_n + v_n \]

- single measurement at time \( n \)
- random mask
- pseudo-random binary sequences with unknown alphabet
- THz-band SLM by photoexcitation of silicon
- Incorporate prior truncated Gaussian mixture model (binary)

- Relatively low cost
- Time consuming
- Needs mechanical scanning

- Relatively high cost
- Time efficiently
- Can cover larger area of code
- Algorithms to recover pseudo-random code

Experimental evaluation

Likelihood Approximation

Iterative variational Bayesian inference (VBI) to recover \( x \) from \( y \)
THz Positioning: 3D QR-code

From THz barcode (Single Track), via THz QR code (Multiple Tracks), to Multi-layer QR code

Non-overlapping, single-layer (front) content

Overlapping, single-layer (front) content

1st layer

2nd layer

3rd layer

Shadowing effect

Curved Sample Surface

~ 0.35 mm

Sweep distortion (due to sample curvature and motor stage vibration)
Deep Learning for THz Sensing

- IRMMW-THz’17/21

Learning-based multi-layer THz imaging

*Data augmentation (invariant to sweep distortion):* augment training data by shifting, attenuating waveforms (a scaling factor), and adding noise

Layer identification (sparse deconvolution – LASSO/FISTA)

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Hybrid Quantum-Classical Neural Network

- Quantum neural network (QNN) is used to support DNN model
Quantum Neural Network (QNN) for Feature Extraction

• Simplified two-design (S2D) ansatz:
  – Staggered Pauli-Y rotations with controlled Z gates
  – Holding statistical properties identical to ensemble random unitaries with respect to the Haar measure up to the first 2 moments: $\text{SO}(2^N) \rightarrow 2N$

• 28 variational parameters:
  – 10-qubits to support 1024-sample signal
Each class ($2^6=64$ in total) covers $10 \times 10 = 100$ pixels (0.5x0.5 mm$^2$) with 4096 time-domain samples for each pixel.

- We randomly split the experimental data for each pixel into training (0.6), validation (0.1), and test (0.3) samples.
- We applied data augmentation to the training dataset including downsampling, shifting, scaling, adding noise, etc.
THz Imaging Results

Shadow Mitigation

Layer #3

Layer #2

Layer #1

Conventional Scheme
(Time-Gated Reflection Intensity)

Logistic Regression
(1194 Params; 87.8% Acc)

Deep Neural Network
(36674 Params; 97.6% Acc)

QML + DNN
(+28 Params; 99.6% Acc)
Conclusions

• We showed recent AI trends overview: ML for everything in community
• We overviewed recent advancement on QML
• We introduced the use of emerging QML for THz imaging
  – Demonstrated the first proof-of-concept study for future quantum-era
  – Experimented the feasibility of QML-assisted THz imaging systems
  – Achieved state-of-the-art performance with few-parameter QML
  – Validated nearly 100% accuracy for 3-layer double-sided imaging
  – Showed gain via hybrid QNN + DNN
• There are many fascinating topics and high potentials for future work
• Questions?
  – Please contact me: koike@merl.com