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Changming Wu
University of Washington

Xiaoxuan Yang
Duke University

Heshan Yu
University of Maryland

Ruoming Peng
University of Washington

Ichiro Takeuchi
University of Maryland

Yiran Chen
Duke University

Mo Li (✉️ moli96@uw.edu)
University of Washington  https://orcid.org/0000-0002-5500-0900

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Harnessing Optoelectronic Noises in a Hybrid Photonic Generative Adversarial Network (GAN)

Changming Wu\textsuperscript{1}, Xiaoxuan Yang\textsuperscript{2}, Heshan Yu\textsuperscript{3}, Ruoming Peng\textsuperscript{1}, Ichiro Takeuchi\textsuperscript{3}, Yiran Chen\textsuperscript{2} and Mo Li\textsuperscript{1,4,*}

\textsuperscript{1}Department of Electrical and Computer Engineering, University of Washington, Seattle, WA 98195, USA
\textsuperscript{2}Department of Electrical and Computer Engineering, Duke University, Durham, NC 27708, USA
\textsuperscript{3}Department of Materials Science and Engineering, University of Maryland, College Park, MD 20742, USA
\textsuperscript{4}Department of Physics, University of Washington, Seattle, WA 98195, USA

ABSTRACT

Integrated programmable optoelectronics is emerging as a promising platform of neural network accelerator, which affords efficient in-memory computing and high bandwidth interconnectivity. The analog nature of optical computing and the inherent optoelectronic noises, however, make the systems error-prone in practical implementations such as classification by discriminative neural networks. It is thus imperative to devise strategies to mitigate and, if possible, harness optical and electrical noises in optoelectronic computing systems. Here, we demonstrate a prototypical hybrid photonic generative adversarial network (GAN) that generates handwritten numbers using an optoelectronic core consisting of an array of programable phase-change optical memory cells. We harness optoelectronic noises in the hybrid photonic GAN by realizing an optoelectronic random number generator derived from the amplified spontaneous emission noise, applying noise-aware training by injecting additional noise to the network, and implementing the trained network with resilience to hardware non-idealities. Surprisingly, the hybrid photonic GAN with hardware noises and inaccuracies can generate images of even higher quality than the noiseless software baseline. Our results suggest the resilience and potential of more complex hybrid generative networks based on large-scale, non-ideal optoelectronic hardware.

* Corresponding author: moli96@uw.edu
demonstrated GAN architecture and the proposed noise-aware training approach are generic and thus applicable to various types of optoelectronic neuromorphic computing hardware.

The current rate of improvement in digital electronics’ energy efficiency\textsuperscript{1–3} is lagging behind the fast-growing computational load\textsuperscript{4,5} spurred by the widespread implementation of large-scale artificial neural networks for machine learning and artificial intelligence\textsuperscript{6–11}. Because of its significant advantages in power efficiency, communication bandwidth and parallelism\textsuperscript{12–19}, analog optical computing based on integrated optoelectronic processors\textsuperscript{20–25} is once again brought into focus as hardware accelerators for neural networks. Photonic neural networks reported to date\textsuperscript{17,20,22,23,26,27} are predominantly hybrid optoelectronic networks in which the photonic components are mainly used for linear multiplication and interconnect while nonlinear functions and feedback control are still implemented electronically. Compared to electronic neural networks using digital processors, such hybrid photonic neural networks have higher inaccuracy and error rates due to the analog nature of computing and the abundance of optoelectronic noises. The accumulation of computational errors in large-scale photonic neural networks could severely impair their performance\textsuperscript{28–30}, limiting the computation effectiveness and scalability. Although several offline noise-aware training schemes have been proposed by injecting noises to layer inputs\textsuperscript{29,31}, synaptic weights\textsuperscript{28,32}, and pre-activations\textsuperscript{33,34} to mitigate analog hardware non-idealities such as inter-device variations\textsuperscript{35,36}, global temporal device performance drifts\textsuperscript{30}, and read/write errors\textsuperscript{21}, they only address discriminative models. Particularly, for a discriminative network based on diffractive optics, training with carefully drafted parametric randomness can make the network robust against sole optical non-idealities such as misalignments\textsuperscript{37}, rescales, shift, and rotation\textsuperscript{38}, but the optoelectronic noises have not been considered. In contrast to discriminative models, generative neural network models can automatically discover and learn regularities or patterns from the training data to generate plausible new instances\textsuperscript{39–41}. They are having a fast-growing range of applications. So far, a photonic generative network has not been reported, and the corresponding noise-aware training strategies aiming to mitigate optoelectronic noises in such networks have not been explored.

Here, we demonstrate a hybrid photonic generative adversarial network (GAN) based on an optoelectronic computing core consisting of a programmable optical memory based on an array of phase-change metasurface mode converters (PMMC)\textsuperscript{42}. We train the photonic GAN to generate
handwritten numbers. Unlike photonic discriminative networks which suffer from noises and errors, in the photonic GAN, we harness and mitigate optoelectronic noises and errors in three ways. First, we utilize the amplified spontaneous emission (ASE) noise to realize an optoelectronic true random number generator\textsuperscript{43,44} (O/E RNG), which is used as the input to the GAN. This O/E RNG efficiently generates random numbers at high speed in multiple parallel wavelength channels by spectrally slicing the ASE spectrums\textsuperscript{44–46}, enabling parallelized photonic generative models. Second, we analyze error sources originating from the optoelectronic components in the photonic GAN and propose noise-aware training approaches by augmenting noises during the training process, which improves the GAN performance and robustness. Third, we validate the training approaches through experiment and simulation, and demonstrate that the photonic GAN can benefit from the inevitable random errors in practical implementation. Surprisingly, the images generated from non-ideal optoelectronic hardware show even higher quality than those generated by an ideal, errorless counterpart (\textit{i.e.}, software baseline). Our results demonstrate the feasibility and resilience of more complex hybrid photonic GANs using non-ideal optoelectronic hardware. Since the proposed noise-aware training approaches are generic, they can be applied to various types of optoelectronic neuromorphic computing hardware.

A GAN network consists of two sub-neural network models (Fig. 1a), a generator and a discriminator\textsuperscript{47–49}. These two models compete against each other in a zero-sum game: the discriminator strives to distinguish the instances produced by the generator (labeled as the “fake” instances) from the real instances in the training dataset (labeled as the “real” instances); the generator aims to fool the discriminator by producing novel instances that imitate the real instances. The competition drives both networks to improve their capabilities until an equilibrium state is reached, \textit{i.e.}, when the “fake” instances are indistinguishable from the “real” instances by the discriminator, so the generator is deemed well-trained to generate plausible new instances. In this work, we design a prototype hybrid photonic GAN to generate images of the handwritten number “7” based on a noise-aware offline training configuration: we first train the GAN on a computer\textsuperscript{50} and implement the trained network model on the photonic platform (Fig. 1b). Here, we only focus on realizing the photonic generator since the photonic discriminator itself is a neural network that performs classification tasks and has been demonstrated previously by many groups, including us\textsuperscript{16,17,20,42}. The kernel matrices stored in the tensor core are mapped onto the PMMCs through electro-optical modulated optical pulses. As shown in Fig. 1c, in each layer of the
generator, the input data is encoded in the power of the optical signals through multiple wavelength channels, processed by the photonic tensor core (Fig. 1d), and the results are detected by the photodetector arrays. Electronic post-processing is then performed to apply nonlinear functions. The results are re-encoded using electro-optic modulators into the optical signals, which are relayed to the next photonic layer. In such hardware implementation of the network, various noises, including optical and electrical noises of the optical sources, modulators and photodetectors, are accumulating through the processes of programming (i.e., writing) the kernel matrices, data encoding, and data transferring (i.e., reading) between the layers of the network.

One key component of the photonic generator is the O/E RNG that produces the random input. To realize it, we utilize the ASE noise from the erbium-doped fiber amplifiers (EDFA), the ubiquitous noise source in fiber-optic communication systems, to generate random optical signals at high rates in four parallel channels, as shown schematically in Fig. 2a. Here, the ASE noise from the EDFA is first filtered with wavelength division multiplexing (WDM) demultiplexers (DEMUX) and then detected with photodetectors. The generated baseband electrical currents due to beating between different frequency components are referred to as “ASE-ASE beat noises”\textsuperscript{51,52}. The DC photocurrent is filtered by a DC block, passing only the stochastic photocurrent variances to a sampling oscilloscope to generate random numbers (see Supplementary Information for the theory of the O/E RNG). Fig. 2b and 2c plot the statistical histogram and a representative trace of the random numbers (in voltage) generated in a single WDM channel, respectively. The probability density function is well-approximated by a zero-mean Gaussian distribution with a standard deviation (STD) of 0.2 V (i.e., $\mathcal{N}(0, 0.2)$). We further calculate the correlation coefficient of an $N=5\times10^4$-number long sequence (Fig. 2d), which reaches the limit of $1/\sqrt{N}$ (red line in Fig. 2d), proving the randomness of the number sequence. Because of the limited size of the photonic tensor core, we measure and record the random numbers from the RNG and repeatedly input them to the generator during the experiment. In future full-scale systems, the filtered ASE noise can be directly used as random input to the GAN.

The other key component of the hybrid photonic generator is the photonic tensor core, which optically performs matrix-vector multiplication (MVM). The inset in Fig. 1c shows the schematic of one PMMC kernel element of the core that computes multiply-accumulate (MAC): $x \to x \cdot w + b$, the fundamental operation of MVM. The PMMC consists of an array of Ge\textsubscript{2}Sb\textsubscript{2}Te\textsubscript{5}
(GST) nano-antennas with tapering widths (see Fig. 1e for the SEM images), forming a phase-gradient meta-surface patterned on a silicon nitride waveguide. The input vector element $x$ is encoded in the power of the input optical signal. The corresponding kernel element weight $w$ is represented using the TE$_0$/TE$_1$ mode contrast $\Gamma = \beta_{TE0} - \beta_{TE1}$ at multiple intermediate levels between [-1..1], where the $\beta_{TE0 (TE1)} = P_{TE0 (TE1)}/(P_{TE0} + P_{TE1})$ is the mode purity, and $P_{TE0 (TE1)}$ is the power of the TE$_0$ (TE$_1$) mode component in the waveguide. Thus, the MAC computation is simplified to an incoherent optical transmission measurement and can be performed over a broad bandwidth. Fig. 2e shows the evolution of $\Gamma$ during the programming process of using optical control pulses to set negative (-0.7), zero (0.0), and positive (0.7) values, respectively. We implement the network model on a 2x2 tensor core with four PMMCs (Fig. 1d). The kernel weight $W_{ijl}$ value is mapped to the corresponding mode contrast $\Gamma'_{ij} = W_{ijl} \cdot (|\Gamma'|_{max} / |W'|_{max})$, where $|\Gamma'|_{max}$ is the maximum absolute mode contrast, $|W'|_{max}$ is the maximum absolute kernel weight of layer $l$. Given the limited number of PMMCs on a chip, we repeatedly reset the kernel elements on the same devices, which bottlenecks the computing speed. With a sufficiently large tensor core in a photonic crossbar array architecture, one could directly map the full kernel matrices to the hardware so the computing speed will be much accelerated.

The analog nature of weight programming and data encoding and transferring in the photonic neural network limits the precisions of MVM calculations and makes the computation error-prone. The computation errors would accumulate through the layers of the network and impair the final results. Because in realistic experiments, the computation errors stem from various optoelectronic noises in the system, we use the terms of noise and error interchangeably. To quantify the noises and errors in our system, we repeatedly program different fixed $\Gamma$ values and estimate the short-term inaccuracy by measuring the variation $\Delta\Gamma$. Fig. 2f shows that the STD of 15 programming operations is less than 0.7%, which is one order-of-magnitude larger than the input encoding error (see Supplementary Material for more detailed error analysis). Thus, the short-term programming inaccuracy $\Delta\Gamma$ (write error), limited by the inaccuracy of the electro-optical modulated optical pulse, is one of the dominant error sources. Another error source is the long-term measurement fluctuations (read error), including the noise of photodetectors, the variation of the O/E and E/O conversions, the thermal fluctuation of the PCM by light absorption,
and so on. These errors collectively contribute to an effective error $\Delta W_{ij}^l = \left(\frac{\Gamma_{ij}^l}{\Gamma_{ij}^{l_{\text{max}}}}\right) \cdot \Delta \Gamma_{ij}^l$ on the kernel element weight $W_{ij}^l$, where $\Delta \Gamma_{ij}^l$ is the total write error. To estimate the computation error of the overall system, Fig. 2g compares the measured MVM error distributions with the simulation, which assumes a Gaussian distribution. The result estimates the overall error $\Delta \Gamma_{ij}^l$ to be 5%, which we subsequently use in the noise-aware training and simulation.

Unlike the discriminative network where the input regularities or patterns are well-defined, the GAN takes random numbers as the input and would be more susceptible to the effective weight setting noise $\Delta W_{ij}^l$, which could degrade the quality of the generated new instances\textsuperscript{56,57}. To reveal the noise effect on the GAN, we emulate the noisy hardware on a GAN model that is trained using a noiseless offline training approach but add a random error $\Delta W_{ij}^l$ (introduced by $\Delta \Gamma_{ij}^l$ with a Gaussian distribution $N(0, 0.05)$) when using it to generate images. Fig. 3a plots 49 images of 14×14 pixels generated from simulation using random inputs produced by the O/E RNG. These images show the handwritten “7” but have very noisy backgrounds, demonstrating that the original training algorithm is impaired by the practical weight setting noise (see Supplementary Information for the detailed comparison between the GAN inference using accurate kernel and inaccurate kernel).

Therefore, it is necessary to take hardware noise into consideration during training to realize a GAN that is resilient to realistic noises. Theoretically, it has been proven that adding noises to the training data of a neural network is equivalent to an extra regularization added to the error function\textsuperscript{31}, which can significantly improve hardware noise tolerance in a discriminative neural network. Meanwhile, it was shown that introducing noise on kernel weights during training enhances the robustness against weight perturbations of multi-layer perceptrons\textsuperscript{28}, and inference accuracy close to the software baseline could be achieved. However, previous demonstrations of noise-aware solutions are limited to discriminative networks. For GAN, theoretical, simulation, and experimental validations of effective noise-aware solutions still lack and require further investigation.

For our hybrid photonic GAN, we propose and experimentally validate two noise-aware training approaches, namely, the input-compensatory approach (IC-GAN) and the kernel weight-compensatory approach (WC-GAN), to improve the tolerance of the network to the effective
weight setting noise $\Delta W_{ij}$. The IC-GAN approach inflates the STD of the random signal input from 0.2 V, the experimental value, to 0.5 V during training. The WC-GAN approach adds $\Delta W_{ij}$ with 5% STD to the corresponding weight at each forward-propagation pass but performs noiseless gradient descent in the back-propagation pass (see Fig. 1b and Supplementary Information for the training procedure for these noise-aware training approaches). Fig. 3b and Fig. 3c show the experimentally generated images of handwritten “7” by the photonic GAN trained using both noise-aware approaches. For a fair comparison, the random number inputs used for inferences are produced by the same E/O RNG. Compared to the images generated by the original GAN (Fig. 3a), the images generated using both noise-aware approaches display much clearer handwritten “7” patterns with lower background noise, thus validating the noise tolerance of the IC-GAN and WC-GAN. Furthermore, we observe the images generated by the WC-GAN (Fig. 3c) have richer handwritten-like features than those by the IC-GAN (Fig. 3b), with more diverse variations in handwritten-like styles. Therefore, we conclude that the WC-GAN is more advantageous for practical implementation using non-ideal analog hardware.

To quantitatively compare the GAN performance, we use the standard metric of Frechet inception distance (FID), which evaluates both the fidelity and diversity of the generated images by comparing the feature distribution in the generated images with images from the training dataset. The lower the FID score, the better performance of the GAN\(^{49}\). In Fig. 3d, the FIDs of the images generated by the original-GAN\(^{35,49,58}\), the IC-GAN, and the WC-GAN, respectively, are compared, assuming either ideal (FID\(_{\text{ideal}}\)) or noisy (FID\(_{\text{noisy}}\)) hardware (see Supplementary Information for detailed steps to calculate the FID). The FID\(_{\text{noisy}}\) (hashed bars in Fig. 3d) is the lowest for the WC-GAN and the highest for the original-GAN, consistent with the observation in Fig. 3a-c. The impact of hardware noise $\Delta \text{FID} = \text{FID}_{\text{noisy}} - \text{FID}_{\text{ideal}}$ is plotted in Fig. 3e. The noise-aware WC-GAN and IC-GAN clearly show two notable benefits. First, the FID\(_{\text{ideal}}\) (solid bars in Fig. 3d) for the WC-GAN is lower than the original-GAN (e.g., the software baseline), indicating that introducing noises during training helps GAN learn better. Such a gain is absent in discriminative networks, where the inference accuracies of the noise-aware trained model cannot exceed the software baseline\(^{29,30,33,34}\). Second, surprisingly, the noise impact results (Fig. 3e) show that, unlike the original-GAN, the WC-GAN and IC-GAN implemented on the photonic hardware with practical noise (hashed bars in Fig. 3d) perform even better in inference than the noiseless hardware (solid bars in Fig. 3d). In contrast, a discriminative network’s inference accuracy always

-7-
decreases with more noisy hardware\textsuperscript{37,38}. This surprising gain in performance suggests photonic neural networks’ potential in generative models despite the inevitable optoelectronic noises and errors.

To predict if the noise-aware approaches performance gain is scalable, in simulation, we train a larger-scaled GAN to generate images of all 10 number digits, using ideal or noise-aware approaches under various levels of writing errors. Fig. 4a shows the FID score of the results as a function of $\Delta I_i^j$. Here, the curvature regularization approach (CR-GAN), which evolves from the WC-GAN, is used to improve the GAN robustness further (see the Supplementary Information for more details about the CR-GAN). The comparison shows that the CR-GAN performs better than the original GAN at every error level. Note that under our present realistic noise level of 5% (Fig. 3g), the FID of CR-GAN is still below the software baseline, whereas the original GAN’s FID is higher than the baseline. For both approaches, with the increasing noise level, the FID first drops until reaching a local minimum at \(~2.5\%\) noise and then increases. To explain this, we further examine the images generated by CR-GAN at three noise levels: 0%, 5%, and 10% in Fig. 4b-d. The comparison shows that the increasing hardware noise in GAN would improve the diversity (evaluated by the STD of the percentage of each number classes in the generated images\textsuperscript{56}, see Supplementary Information for more details) but at the same time reduce the fidelity of the generated images\textsuperscript{56}. The trade-off results in a minimal FID at \(~2.5\%\) noise as in Fig. 4a. Throughout the full range of noise levels, the noise-aware approach consistently improves the GAN over the noiseless approach.

In conclusion, we demonstrate a hybrid photonic GAN network based on phase-change photonics by utilizing the intrinsic noise sources in the photonic system. Unlike the previously demonstrated discriminative networks that suffer from the hardware noise, our experimental and simulation results show the photonic GAN can not only tolerate but also benefit from a certain level of hardware noise when using noise-aware training approaches. Our finding expands the current implementation of photonic neural networks to generative models\textsuperscript{59}, in which the inevitable and ubiquitous optoelectronic noises and errors can be mitigated and even leveraged in intelligent ways. We emphasize that the proposed noise-aware training approaches are generic and thus applicable to various types of optoelectronic neuromorphic computing hardware, the improved resilience of the proposed model designs to the noises also implies their scalability in large-scale hybrid neural networks with tightly co-integrated electronics and photonics.
**FIGURES**

**Figure 1 Photonic GAN network with optoelectronic noises.**

a. The general GAN framework is composed of two sub-network models, a generator and a discriminator. The generator competes with the discriminator during training and could generate new instances after it is trained.

b. The offline noise-aware training and inference processes flow of the generator. While mapping the trained weight to the hardware during the implementation, the optoelectronic noise is inevitably introduced.

c. Decomposition of the generator into individual layers. In each layer, the input signals pass through the photonic tensor core and are converted to the electrical domain by photodetectors (PDs). After post-processing, the data is converted back into the optical domain and then transferred to the next layer.

d. Optical microscopic image of the photonic tensor core consisting of four input channels.

e. The detailed false-colored SEM image of the photonic tensor core. The Si$_3$N$_4$ waveguide, the GST metasurface and the Al$_2$O$_3$ protection layer are colored green, red, and blue, respectively. Scale bar: 10 μm. Inset: the zoomed-in SEM image of the phase-gradient metasurface on the waveguide. Scale bar: 2 μm.
Figure 2 Optoelectronic RNG and kernel programming errors. a. Schematic of the optoelectronic RNG. The ASE noise is spectrally sliced into 4 wavelength channels using DEMUX and then detected with square-law photodetectors. After a DC block, the random electrical signals are sampled by an oscilloscope. b. and c. Statistical histograms (b) and a representative trace (c) of the generated random numbers. The generated random number follows the Gaussian distribution. d. Correlation coefficient as a function of lag for the random number sequence. A random number sequence with length $N = 5 \times 10^4$ has a correlation coefficient (blue dots) around the lower limit $1 / \sqrt{N}$ (red line). e. Process of programming the mode contrast of a kernel element using optical pulses. The target $\Gamma$ values are -0.7, 0, and 0.7, respectively. f. Histogram of $\Gamma$ value distribution when the kernels are repeatedly set to be -0.7, 0, and 0.7, respectively. The standard deviation for each setting is 0.37%, 0.67%, 0.68%, respectively. g. Histograms of the error distribution obtained by experimental measurement (solid) and the simulation (hashed) when assuming the $\Delta \Gamma_{ij}$ follow a Gaussian distribution with a standard deviation equal to 5%. Inset: Measured MVM accuracy for 4900 MVM operations in the first layer of the network.
Figure 3 Generating handwritten numbers with GAN. a-c: 49 images (size: 14×14 pixels) generated by (a) original-GAN, (b) IC-GAN, and (c) WC-GAN under effective kernel weight setting error (introduced by 5% Gaussian random error ΔΓij) using random inputs~ N(0,0.2) produced by the O/E RNG. (a) is generated by simulation, (b) and (c) are the outputs from experiments. d. The FIDs of the generated images assuming the network is trained using various approaches and is implemented either on the ideal (solid bars) or noisy practical hardware (hashed bars). The FIDs obtained from the experimental results are labeled as stars. e. The ΔFID of the images generated by the same GAN using the same random input but performing inferences using a noiseless (simulation) or practical hardware (simulation and experiment), respectively. The ΔFIDs calculated from experimentally generated images are denoted by the red lines.
Figure 4 Scalability of noise-aware training. a. The FID of the generated images by original GAN and CR-GAN respectively under various effective mode contrast setting noise $\Delta \Gamma_{lij}$ with STD ranging from 0% to 10%. The shaded region indicates the range of FID over 5 individual tests. The FID is lower for CR-GAN at every noise level. Under 5% practice noise (black dashed line), the FID for CR-GAN is below the software baseline (solid green line) while the FID for the original GAN is above it. b-d: 50 images (size: 14×14) generated by curvature-regularization GAN assuming under effective mode contrast setting noise of (b) 0%, (c) 5%, (d) 10%.
Reference:


Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryInformationv3.pdf