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Wave-based neural networks trained by unsupervised physical local learning

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Deep learning has become a breakthrough technology with remarkable success, primarily operating on traditional von Neumann computing hardware. As demand for deep learning continues to grow, there is an urgent need to develop high-speed and energy-efficient accelerators. While electronic processors such as GPU are versatile, researchers are exploring more efficient ways to use Analog Neural Networks (ANNs) on different physical platforms such as optics, spintronics, photonics, and acoustics [1]. The training of such physical neural networks (PNNs) has conventionally hinged upon the utilization of backpropagation (BP) as a primary method. However, BP manifests as an ill-suited choice for PNNs, primarily due to the intricate and non-scalable nature of its implementation within physical hardware configurations [2]. A common workaround is in-silico training, where we do BP calculations on a digital replica of the physical system. However, this method may result in potential simulation-reality gaps due to inaccurate representation of the physical system. Recent advances have tried to solve these issues. One promising development is a physics-aware training method using BP, which helps with some of the problems of in-silico methods [3]. However, it still relies on a digital model for the backward pass, which limits its speed, energy efficiency, and memory requirements. Also, PNNs trained with this method can be sensitive to system changes, possibly needing complete retraining. Another limitation of BP is that it requires complete knowledge of the computation graph carried out during the forward pass to compute derivatives.

The concept of local learning has been extensively explored in the context of digital neural network training, spanning from early investigations into Hebbian contrastive learning within Hopfield models to more recent biologically plausible frameworks, blockwise backpropagation, and contrastive representation learning [4]. Inspired by this paradigm and motivated to overcome the limitations inherent to BP-based PNN training, we have proposed a physics-compatible PNN architecture, augmented by an unsupervised physical local learning paradigm denoted as UPhyLL. Our approach empowers the training of diverse PNNs without necessitating a comprehensive understanding of the nonlinear physical layers or the reliance on a digital twin model. UPhyLL supplants the traditional digital backward pass with a solitary forward pass through the physical system, thereby markedly enhancing training speed while simultaneously diminishing digital computational demands, memory utilization, and power consumption within wave-based PNNs.

To show the universality of our approach, we presented experimental results encompassing vowel and image classification using three distinct wave-based systems, each characterized by unique wave phenomena and nonlinearities. These systems encompass (i) a chaotic acoustic cavity replete with nonlinear scatterers, (ii) a chaotic microwave cavity parameterized by a programmable metasurface featuring structural non-linearity, and (iii) an optical multimodal fiber with readout non-linearity. Our method not only exhibits advantages over alternative hardware-aware training strategies but also augments training speed, bolsters robustness, and curtails power consumption by obviating the necessity for system modeling, thereby concomitantly reducing digital computational overhead.

References:

[1]. A. Momeni, & R. Fleury, "Electromagnetic wave-based extreme deep learning with nonlinear time-Floquet entanglement". *Nature Communications*, 13(1), 2022, pp. 2651.

[2]. Pai, S., Sun, Z., Hughes, T. W., Park, T., Bartlett, B., Williamson, I. A., Minkov, M., Milanizadeh, M., Abebe, N., Morichetti, F., et al., "Experimentally realized in situ backpropagation for deep learning in photonic neural networks," *Science*, 380(6643), 2023, pp. 398–404.

[3]. L. G. Wright, T. Onodera, M. M. Stein, T. Wang, D. T. Schachter, Z. Hu, P. L. McMahon, "Deep physical neural networks trained with backpropagation," *Nature*, 601, 2022, pp. 549–555.

[4]. Momeni, A., Rahmani, B., Mall´ejac, M., Del Hougne, P., and Fleury, R., "Backpropagation-free training of deep physical neural networks," Science 382(6676), 2023, pp. 1297–1303.