Optical Convolutional Neural Network with Atomic Nonlinearity

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Abstract: An optical convolutional neural network is demonstrated in which linear operations are implemented by lenses and digital micro mirror devices, while an optical nonlinearity is realized by cesium atoms as a saturable absorber. This system classifies the handwritten digital dataset MNIST [1] with 83.96% accuracy, which agrees well with corresponding simulations. Our results thus demonstrate the viability of utilizing atomic nonlinearities in neural network architectures with low power consumption.

Convolutional neural networks (CNNs) have become an indispensable part of machine learning due to their successful application on image-based machine learning problems. However, the compute resources required to train and infer such CNNs scale quadratically with problem size, thus expense of time and energy is large. Unlike electrons, photons can be used to naturally realize massive and parallel interconnections [2], achieve clock speeds in the GHz range and most importantly the computational cost for optical convolutions scales only linearly with problem size. Thus, optical computing is becoming ever more attractive. Within the broader context of artificial neural networks, linear-optics implementations can be realized through free-space or integrated methods. The former encompasses diffractive materials and spatial light modulators (SLMs), etc., while the latter involves phase-change materials and semiconductor optical amplifiers, among others. Mechanisms for achieving optical nonlinearity include atom-based nonlinearities, saturable absorption in thermal atoms, and electromagnetically induced transparency, as well as solid-state approaches such as the use of phase-change materials. Here we demonstrate an optical convolutional neural network (OCNN) in which both linear operations and the nonlinearity are realized optically. The handwritten digit dataset MNIST is used to train and benchmark the OCNN.

We implement the OCNN with one input layer, one optical convolutional layer, one fully connected layer followed by one output layer. An optical nonlinearity is applied after the convolutional layer [Fig. 1]. The OCNN performs the convolution process by employing the convolution theorem

$$f(x) * h(x) = \mathcal{F}^{-1}\{\mathcal{F}[f(x)] \cdot \mathcal{F}[h(x)]\} \tag{1}$$

and the Fourier transform properties of lenses. Specifically, the convolution ($*$) of the input $f(x)$ and the kernel $h(x)$ is the inverse Fourier transform ($\mathcal{F}^{-1}$) of the pointwise product ($\cdot$) of their Fourier transforms ($\mathcal{F}[f(x)], \mathcal{F}[h(x)]$). These individual parts can be performed optically and passively by constructing a 4f-system with two digital micromirror devices and two lenses. Thus, the convolved images can be observed in the front focal plane of the second lens. A CMOS camera acts as an analog-to-digital converter. A digital fully connected layer is implemented in the computer to connect the nonlinear activated feature maps and the output layer. We simulate the system based on the experimental setup, which is used to train both the kernel of the OCNN and the digital fully connected layer. The trained kernel is then

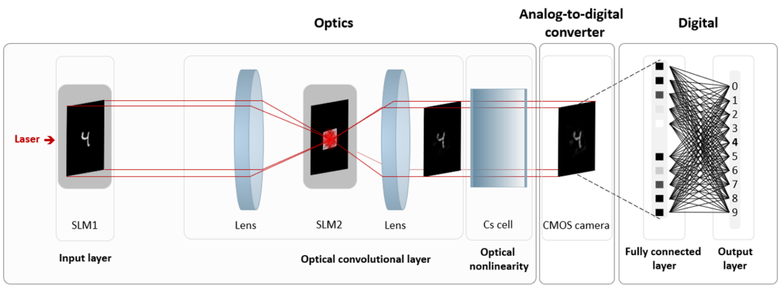

Figure 1: Sketch of the experimental setup.

displayed in the experiment and the inference process is executed for both simulation and experiment, for the same kernel and fully connected layer. In the experiment, the optical nonlinearity is provided by a cesium vapor cell. The cesium atoms absorb on-resonant photons and are excited to the excited state.

This absorption process results in attenuation of the intensity of the beam passing through the atoms. The relation between the output intensity I and the input intensity I_0 is

$$I = I_0 \exp\left(\frac{-\mathrm{OD}_0}{1 + I_0/I_s}\right), \tag{2}$$

where I, I_0, I_s represent the output intensity, input intensity, and saturation intensity, respectively. The optical depth at $I_0 = 0$ is given by OD_0.

When the input intensity I_0 reaches the saturation intensity I_s, the absorption is reduced by 50%. The input-output relation thus follows a nonlinear shape. While varying the incident laser power to the cesium vapor cell, we measure the resulting pixel intensity detected by the CMOS camera with and without the Cs cell, respectively. The measured and fitted input-output relation of the nonlinearity is used to provide the optical nonlinearity for the OCNN [Fig. 2].

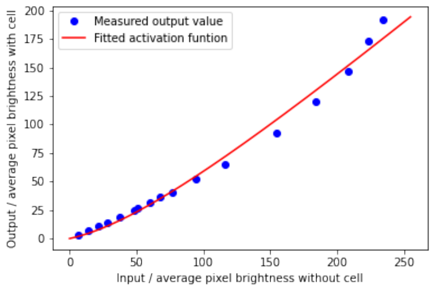

Figure 2: Measured input-output average pixel brightness and the corresponding fit curve. Fitting the experimental data to Eq. (1) gives $OD_0 = 1.38, I_s = 62.31$ pixel brightness. The axes represent the average grayscale value of the picture without (input) and with (output) the vapor cell, respectively.

The prediction accuracy of the OCNN setup for recognizing the MNIST are summarized in Table 1. The simulation of the OCNN achieve 92.6% and 93.2% accuracy with the cesium absorption function and the ReLU function as nonlinearity, respectively. The OCNN setup achieves 70.72% and 71.84% accuracy with and without the vapor cell in the setup, respectively. We train a mapping matrix using the full 10,000 test data being processed by the optical system. This linear mapping is used to modify the fully connected layer, i.e. to retrain it to the experimental data. With the help of this training, the accuracy increases to 83.96% and 91.9% as a result of with and without the vapor cell, respectively.

Non-linearity	Cs Vapor	ReLU	No nonlinearity
Simulation	92.6%	93.2%	90.8%
OCNN (No mapping matrix)	71.84%	70.72%	45.59%
OCNN (With mapping matrix)	83.96%	91.9%	89.3%

Table 1. Summary of OCNN prediction accuracy. Each kernel is individually trained for each case. No nonlinearity means that no additional nonlinearity is added beyond the inherent nonlinearity of the camera.

In summary, we have demonstrated an optical convolutional neural network with atomic nonlinearity. The effectiveness of the atomic vapor cell suggests that it has great potential to provide optical nonlinear activation functions for neural networks with other topologies. It is an attractive candidate for use in multilayer optical neural networks with several SLMs and vapor cells in series. Moreover, the atomic nonlinearity enables the possibilities for realizing multilayer ONNs with all-optical training [3].

References

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