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Deep Classification from Scattered Light

Sara Peña-Gutiérrez [1,*] and *Marco Leonetti* [2]

[1]Center for Life Nano- & Neuroscience, Italian Institute of Technology, Viale Regina Elena 291, I-00161, Rome, Italy
[2]Institute of Nanotechnology of the National Research Council of Italy, CNR-NANOTEC, Piazzale A. Moro 5, I-00185, Rome, Italy

Abstract. Photonic Stochastic Emergent Learning (PSEL) represents an innovative paradigm rooted in mathematical brain modelling and emergent memories. In this study, we explore the intersection of these concepts to address memory storage and classification tasks. Leveraging optical computing principles and random projections, PSEL constructs memory representations from the inherent randomness in nature. Specifically, we select a set of highly similar random states generated by coherent light scattered from a diffusive medium. Classification is performed by organizing the memories spatially into different classes and comparing inputs to those stored memories. The results demonstrate the efficacy of PSEL in memory construction and parallel classification, emphasizing its potential applications in high-performance computing and artificial intelligence systems.

1 Background

Deep classification, a fundamental task in machine learning, involves categorizing data into distinct classes using deep neural networks (DNNs) [1]. These networks, inspired by the human brain, consist of interconnected layers that learn hierarchical features from raw input data. As deepening into the layers, the representations become more abstract. Deep classification finds applications in image recognition [2], natural language processing [3], healthcare diagnostics [4], and more [1,5]. However, managing large datasets poses a significant challenge, requiring substantial computational resources and memory. Here, optical hardware emerges as a solution.

As deep neural network (DNN) models grow larger, electronic processors face limitations in scaling due to communication costs, thermal management, and power delivery. Optical systems allow massive parallelism due to the inherent nature of light, unlike electronic circuits, which process information sequentially. By leveraging the unique properties of light, optical systems offer parallelism, energy efficiency, and robustness, enabling efficient processing of vast amounts of data.

Many novel optical architectures have been developed addressing the problems in deep classification from different approaches. Researchers studied the use of passive diffractive layers to perform handwritten digit classification [6], enabling all-optical image analysis, feature detection opening new possibilities for camera designs and optical components. Another approach consists in develop analogic optical-based co-processors, to complement the existing silicon-based chips. Researchers implement optically random projections solution for classification tasks [7,8]. The random projections are generated with an analogic optical device at the speed of light without storing any matrix in memory by taking advantage of the multiple coherent scattering of coherent light in random media. This framework makes machine learning practical for applications with large training sets and real-time prediction. A different line of action consists in developing a brain-inspired photonic computer, based on the reservoir computing paradigm. It requires both training and classification and achieves state-of-the-art accuracy in human action recognition from video streams [9]. A diverse perspective is developed in [8] where researchers develop a programmable optical hardware capable of store memories and perform classification at the speed of light. This optical hardware is inspired by the modelling for brain function, particularly the Hopfield network, the ability of learning from imperfect input examples, together with the physical process of light scattering. This last approach is a novelty with respect to previous research since the training on the dataset is performed at the speed of light based on random transmission matrices.

In this communication, we present a new brain inspired and photonic based light platform to perform deep classification tasks based on the Stochastic Emergent Storage [8] for deep classification. We will explain the working concept of SES and its application to classification of images together with latest results on MNIST dataset [10] for evaluating the hardware performance.

2 Photonic stochastic emergent learning

The Stochastic Emergent Storage is inspired from the mathematical modelling of brain function. Hopfield networks use a synaptic matrix to interconnect the neurons. Memory storage in brain is recently explained from the emergent archetype, where a memory is built

* Corresponding author: sara.penagutierrez@iit.it

from non-perfect pieces. Photonic Stochastic Emergent Learning (PSEL) is settled down by combining these two conceptions, together with previous research in optical computing [9] using random projections. Photonic SES constructs an emergent description of the desired memory from the abundance of randomness in nature. For this reason, a set comprising the highest similar random states produced by the scattered coherent light from a diffusive media is selected and the weighted sum of their optical transmission matrix is calculated to generate the desired pattern. Classification is achieved by simultaneously comparing an input to all memories stored in the system [8], which function as features. Thus, the system can perform parallel classification reducing the time of computation.

2.1 Experimental set-up

The PSEL is implemented by using a monochromatic laser at 532 nm that illuminates a digital micromirror device (DMD), able to spatially encode digital information on the light beam by amplitude modulation composed by 1024 x 768 micromirrors (Vialux, V-7000). Phase modulation is achieved by employing the superpixel method [11]. The light beam carrying the signal is then focused on a random medium by a lens. Here, the medium is a 60 µm layer of ZnO (Sigma Aldrich 544906). The transmitted light is collected on the far side by a second lens and is measured by a standard monochrome CCD camera. Further details found in [8].

3 Classification results

Classification performance is evaluated using the MNIST handwritten digit dataset. A pre-processing should be addressed before projecting the pattern with the DMD. Each digit in the MNIST dataset can be seen as a 28^2 array of integers between 0 and 255. We first quantized the grey levels between 0 and 1. We then encoded each of these quantized pixels as a 4 x 4 super pixel array of DMD micro-mirrors.

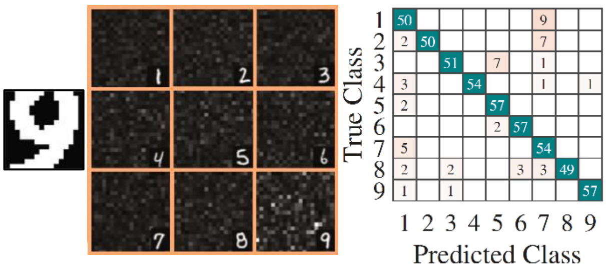

Fig. 1. (a) Diagram showing the intensities of input pattern (left) relative to the stored memories organized in quadrants (21 x 21 for each class). (b) Confusion matrix for the categorical classification.

A dataset containing 4500 digits from the MNIST repository, organized into 9 categories (representing digits from 1 to 9), was used for assessing the system. Within the disordered classifier, 3969 patterns or features were stored (with 441 per digit), leaving 59 patterns per category for validation. By employing a DMD with a 33kHz frame rate, the system essentially performs optical classification in just 0.1 seconds. In the camera-like diagrams (as shown in Figure 1a), each category corresponds to a specific quadrant of the image. The panels display the response of the disordered classifier to input data, with the corresponding quadrants showing a high concentration of intense pixels. Additionally, Figure 1b presents the confusion matrix for all labels, demonstrating categorical recognition efficiency above 90%. Further improvements can be achieved by employing error correction algorithms. Overall, this result highlights the potential to create deeper optical machine learning architectures and perform training by grouping memories.

4 Conclusions

Optical hardware advancements play a crucial role in enhancing deep classification by leveraging the unique properties of light. In this communication, the PSEL has been demonstrated to be a novel method to speed up classification tasks using emergent random archetypes from light scattering. Integrating optics with deep learning can enhance the performance while addressing critical limitations associated with managing large datasets.

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