LIGHT FIELD NEURAL NETWORK

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ABSTRACT

We introduce an optical neural network system made by off-the-shelf components. Compared to electronic systems, the proposed system can execute advanced inference tasks on the speed of light and much lower power consumption. By using see-through screens and optical components, it can support a programmable optical neural network, see-through display, and incoherent light processor. Various application prototypes are discussed as extensions of basic layers including optical computation, light field display, augmented reality, and passive light/image processing.

Keywords Deep learning · Optical neural network · Light field display · Virtual reality · Augmented reality · Mixed reality · Passive light/image processing

1 Introduction

Recently, deep learning and deep neural networks (DNNs) have got growing interests and utilities in various areas LeCun et al. [2015]. General purpose or specifically tailored electronic processors are used to execute the inference tasks, and well known examples include traditional central processing units (CPU), graphical processing units (GPU), application-specific integrated circuits (ASICs), and field-programmable gate arrays (FPGAs).

While the electric processors have shown great performance for DNNs, they have common inherent issues such as size, power consumption, computation cost and latency. These issues may not cause a significant problem for desktop PCs, but restrict their utilities in embedded, mobile, light weight, and real-time systems.

New effort has been directed toward the development of artificial neural networks (ANNs) to overcome these limitations. Fully optical neural networks (ONNs) offer a promising alternative approach thanks to the inherent parallel computing capability and power efficiency of optical systems Shen et al. [2017], Lin et al. [2018], Chang et al. [2018].

In this work, we propose to use a novel, light field modulation technique to build a Light Field Neural Network (LFNN), a novel ONN system based on common display panels (e.g., OLED panels) and optical components (e.g., lens). The proposed LFNN is an innovative device, since it is a device that can serve all the functions of programmable ONN, see-through display system, and incoherent light processor. It can directly process and display the light signal at once. This distinctive characteristic makes it a promising approach for many applications, such as optical computation, virtual reality (VR), augmented reality (AR), mixed reality (MR), 3D or light field display, lens enhancement, display enhancement, and passive light/image processing.

Overall, our main contributions are summarized the following: we propose novel structures that consists of incoherent additive layers (OLED), attenuation layers (lyquid-cristal layers) and scattering layers to create a new kind of devices, which combine the function of processor and display system with merits of high performance, lightweight, low power consumption, nearly zero latency/computational cost and ultra-high resolution/frame-rate.

2 Light Field Neural Network Structure

In this section, we discuss how to design a basic layer and its improvement based on off-the-shelf optical components.
2.1 Basic Layer

The basic neural network has the following propagation function:

\[ x^{j+1} = f(W^j x^j + b^j), \]

where \( x^j \) and \( x^{j+1} \) are neurons of two successive layers, \( W^j \) is the propagation weights connecting those two layers, \( b^j \) is a bias vector, and \( f(x) \) is usually a nonlinear function. Previous ONN approaches used complex nanophotonic circuits or diffraction layers to simulate these operations [Shen et al. 2017, Lin et al. 2018, Chang et al. 2018], but inevitably introduced unpleasant coherence issue, phase encoding/decoding noise or loss of programmability.

Instead, we propose to use readily available incoherent screens and optical components to modulate the layer (Figure 1). The scattering layer is made by diffuse or (optionally) nonlinearly transmission material (e.g. crystal) to gather and propagate energy within sequential layers as virtual neurons (Figure 2). The number and size of virtual neurons can adapt to various neural network applications. The bias layer and addition operation can be simulated by transparent Organic Light-Emitting Diode (tOLED) layer or holographic optical elements (HOEs) [Chung et al. 2015, Lee et al. 2016]. Finally, multiple liquid crystal layers with polarizers can compose an attenuation matrix to serve the function of matrix multiplication by decomposing the target matrix \( W^j \) into multiple layers [Huang et al. 2015]. For function \( f \), we can use non-diffuse transmission material to introduce nonlinearity. Because the weights and bias between layers are modulated by light field synthesizing techniques and the signal is transported between neurons through light, we call our approach light field neural network (LFNN).

2.2 Advanced Neural Network

Multiple improvements can be supported on the basic layer to enhance the utility of LFNN. Adding phase encoding pattern [Peng et al. 2017] in the scattering layers can introduce a negative operation, which can help improve neural network accuracy [Chorowski and Zurada 2015]. Absorption materials (e.g., Jutamulia et al. 1993) can serve the same purpose.

Even tough dynamic LFNN layers (OLED, liquid-crystal and scattering layers) has many merits (e.g., dynamic, incoherent and see-through), one possible problem is that the OLED and liquid-crystal layers might affect the power efficiency. We thus propose to use a hybrid module putting static diffraction pattern layers (e.g., holograms [Peng et al. 2017]) to modulate the layer's attenuation.
in front of dynamic LFNN layers to improve the power efficiency. The static layers can be trained by neural network modularization techniques (e.g., Vogels et al. [2018] as general geometry feature extractor, then followed by dynamic LFNN layers for various applications (Figure 3).

3 Applications

The proposed LFNN system is composed of neural network, display and incoherent light processor, and it can be easily integrated with various input/output to provide promising quality/utility/performance/power/latency progress in different areas.

3.1 Optical Computation

A basic application of LFNN is optical computation (Figure 4(a)). By embedding a high-speed light source and a detector in two sides of LFNN, the system can serve as a optical inference computer with the speed of light and very low power consumption. Since the system can propagate signals in parallel, the process speed is determined by the speed of light source and detector; high-end light source and photon detector can provide THz inference speed Lin et al. [2018]. For embedded and mobile utility, ultra high-speed micro LED display and CCD/CMOS sensors can reach GHz inference speed McKendry et al. [2010], Etoh et al. [2013].

3.2 Light Field Display

Resolving the vergence-accommodation conflict in head-mounted displays (HMD) is one of key challenges for VR/AR/MR applications Kramidal [2016]. While light field displays present a promising approach, the spatial/angular resolution and computational overhead are two major challenges. Synthesizing a 4D light field neural network requires a large GPU bandwidth. In addition, displaying the synthesized 4D signal with high spatial and angular resolution is even more challenging.

An important advantage of LFNN is that it is both neural network and display system. In theory, we can combine a light field synthesizing neural network Yoon et al. [2017] and a light field display Huang et al. [2015] together in the
framework of LFNN (Figure 4(b)). The advantage of the display system includes nearly zero synthesizing overhead and dramatically large resolutions, thanks to multiple display layers (OLED, liquid crystal, scattering layers and background screen) providing a large amount of free parameters for modulating the light field by scattering the light in various distances.

Compared to the basic LFNN, a major hardware modification is a controllable scattering layer (e.g., PDLC glass), resulting in freely mixing scattered lights from various layers to simulate real world light fields. A similar idea can also be used to build a 3D display.

3.3 AR/MR Display

Another important application of LFNN is AR/MR display system. The primary advantage is that it can directly process the real-world light signals without DC/CD transformation and computation, leading to nearly zero latency, computation overhead and power consumption. These characteristics make it a competitive approach for real-time and light weight AR/MR display (e.g., vehicle windshield and AR/MR glasses). With a controllable scattering layer and polarizer, LFNN can blend real world and virtual world together through time-multiplexing techniques [Lanman et al. 2010, Wetzstein et al. 2011, Maimone et al. 2014].

3.4 Passive Light Processor

Because LFNN can directly process incoherent light, it can work as an passive image processing system. For example, we can put a light enhancement neural network in front of camera to capture details in dark rooms [Chen et al. 2018], put a denoising neural network [Vogels et al. 2018] in front of a screen to remove rendering noises without a GPU overhead, and use a self-encoding neural network in front of a sensor to capture real-world light field and display it with a decoding neural network, and so on.

4 Conclusion

We have propose an incoherent optical neural network based approach for optical computation, display and light processing. The advantage of the system includes nearly zero latency/computation, low power consumption, light weight, concision, and high-dimensional display ability. As a combination of optical neural network, display and light/image processor, we believe that it provides many promising possibilities for VR/AR/MR industry.
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