

Time Delay Optical Neural Network

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Abstract – An efficient optical architecture for implementing a time delay optical neural network utilizing acoustooptic devices, scrolling CCD detector arrays, and photorefractive weight storage is presented.

1 Introduction

Time delay neural networks (TDNN) generalize the weighted interconnections used in conventional neural networks to finite impulse response (FIR) filters between each pair of connected neurons.¹ The weight matrix that describes the connectivity of conventional neural networks is replaced by a 3-D array of FIR filter tap coefficients between pairs of neurons. For a network with a thousand neurons and filters with a thousand taps this results in 10^9 FIR weights as compared with only 10^6 weights in a conventional neural network. The rapid access to these stored FIR weights and their use as weighted and delayed interconnection coefficients can require computational throughputs of a TFLOP or more, and this presents an excellent opportunity for the use of highly parallel optical techniques. In this paper we present an efficient architectural approach to the implementation of TDNN using readily available components.

Previously an optical TDNN has been demonstrated using an elegant rotating photorefractive crystal (PRC) approach to producing a continuous array of delayed inputs and delayed hidden layer neuron activities with the capabilities for auditory bandwidths and acoustic speech processing, and this approach even allows dynamic learning of patterns.² An efficient pipelining of the synthetic aperture radar (SAR) problem using hybrid time-and-space integration (TSI) with acoustooptic (AO) devices and time-delay-and-integrate (TDI) CCDs³ is the precursor to the TDNN architecture presented here. The TSI approach to optical TDNNs presented here uses space integration across the input neurons and TDI temporal accumulation of the FIR filters. This approach is designed to be an efficient match with readily avail-

able technologies (AO, CCD, PRC), which allows processing of high speed data (eg radar rather than acoustic bandwidths) with massively parallel internal computation harnessing 3-D storage of weights in photorefractive crystals, allows high speed time delay operation using TDI CCDs without the bandwidth restrictions of mechanical motions, and has simple input and output electrical interfaces.

2 Time Delay Neural Networks

Time delay neural networks are typically utilized for processing time varying signals such as acoustic speech waveforms, where a preprocessing step converts a single signal into a spatio-temporally evolving array of signals such as the time varying spectrogram.

$$y_m^j = \left| \int w(t - j\Delta) s(t) e^{i2\pi t m/T} dt \right|^2 \quad (1)$$

where $w(t)$ is a window function of width on the order of Δ used for each spectral calculation that slides over the input signal $s(t)$. At each time step $T = j\Delta$ the most recent D spectral slices are utilized by the network, so that a scrolling spectrogram is used as the dynamic input. Alternatively when an array of time varying signals is available (such as from an array of M sensors), their D delayed samples can be used as inputs. The general formulation of a multilayer TDNN can be written as a FIR filtering on the outputs of the l th layer,

$$y_{it}^{l+1} = f \left(\sum_j \sum_{k=0}^D y_{jt-k}^l W_{ijk} \right) \quad (2)$$

A causal temporal back propagation algorithm can be used for pattern recognition or for sophisticated temporal prediction learning tasks.¹

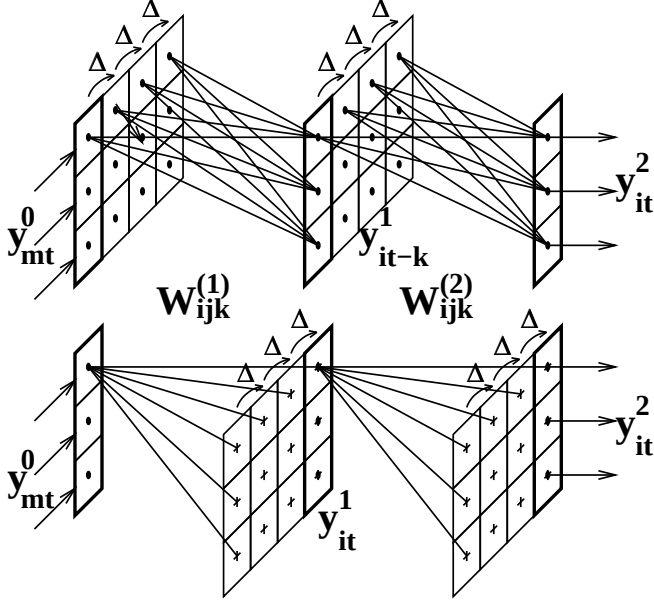


Figure 1: Time delay neural network topology and the equivalent FIR filter neural network topology utilized for the optical architecture.

3 Optical Implementation

Scrolling SLMs would allow a direct implementation of the TDNN formulation presented in the previous section, and the rotating photorefractive crystal technique was based on this interpretation. The ready availability of high quality scrolling TDI mode CCD detector arrays leads us to an alternative formulation shown in Figure 2. This system is designed to provide the same functionality of the acoustic spectrogram processors envisioned for the original TDNN, but to achieve this processing at radar bandwidths of up to 1GHz compatible with AO device technology. Typical doppler bandwidths corresponding to variations of the radar returns on a pulse to pulse basis are on the order of 10KHz and are commensurate with CCD TDI shift rates. For example, for time varying wideband spectrogram based processing the input signal is applied to an AOD whose output is spatially Fourier transformed to produce the angular multiplexed readout beams of a multiply exposed volume hologram.

$$S(t, u) = \int_A s(t - x/v) e^{i\omega(t - x/v)} e^{-i2\pi xu} dx e^{i2\pi\nu_0 t} \quad (3)$$

where v is the acoustic velocity $u = x'/\lambda F$ is the normalized spatial frequency variable, F is the lens focal

length, $\lambda = c/\nu_0$ is the laser wavelength, and ω is the RF carrier. Each of these spectral amplitude coefficients reads out an angularly multiplexed hologram (where unlike normal volume holographically stored images, in this case the images are barely resolved and continuously varying with position x') which is imaged onto the CCD. The CCD detects the time integral of the incident intensity before each discrete vertical spatial shift,

$$I(x, y, k) = \int_{k\Delta}^{(k+1)\Delta} \left| \int S(t, u) W^{(1)}(u, x, y) du \right|^2 dt. \quad (4)$$

Spatially shifting by one pixel of width h in the y direction and subsequent integrations accumulate in the TDI moving coordinate system whose velocity is $V = h/\Delta$, gives an output

$$\begin{aligned} o(x, k) &= \sum_{j=(k-D)}^k I(x, y - jh, j) \\ &\approx \sum_{j=0}^D \int |S(k - j, u)|^2 W(u, x, jh) du \end{aligned} \quad (5)$$

In this expression $|S(k, u)|^2$ represents the effective spectral slice input during the k th interval, and W is the effective intensity diffraction efficiencies of the angularly multiplexed holograms for the u th reference position on the j th line. After TDI accumulation, each video line output from the CCD produces a sequential rastering of the neurons. Adjacent complementary excitatory and inhibitory channels can be subtracted to accomplish bipolar operations and to remove the unavoidable bias due to the time integration. A single saturating amplifier can accomplish all the required neuron nonlinearities sequentially. The thresholded output is mixed to the center frequency of a second AOD, and slid into the device aperture. A synchronized pulse from a Q-switched laser freezes the acoustic motion, producing a spatial modulation on the k th pulse $O(x, k) = f(o(x, T = k\Delta))$. Each frozen neuron output acts as the angularly multiplexed plane wave reference beam to a second multiply exposed photorefractive volume hologram that produces an accumulated diffraction on a second TDI CCD. A reference beam can be included for coherent detection if linear response in field amplitude is required.

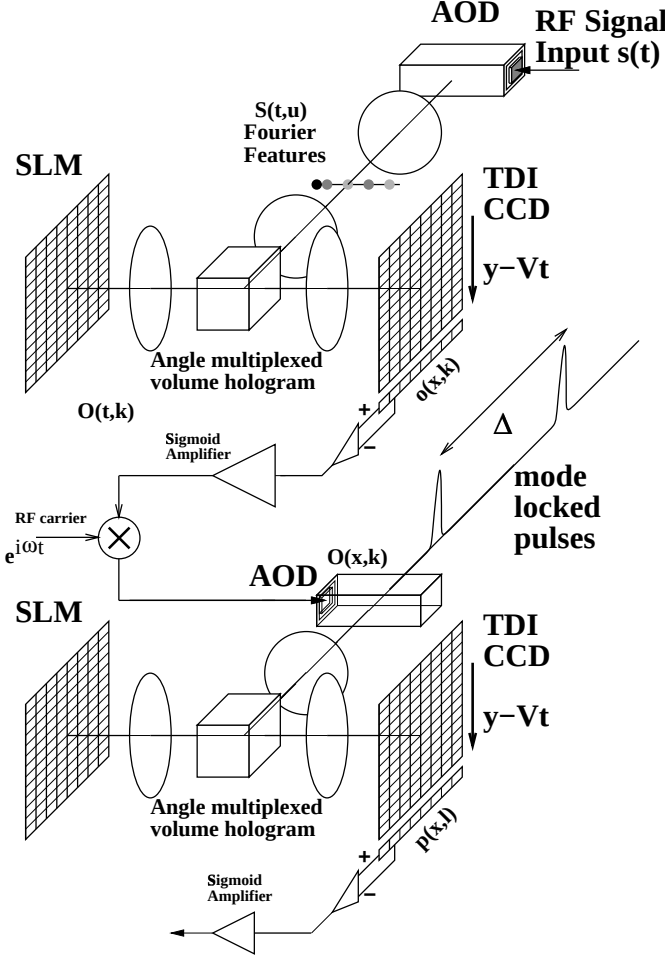


Figure 2: Two layer time-delay optical neural network to process radar spectrogram evolution.

The resulting output of the second layer is given by

$$p(m, T = l\Delta) = \sum_n \sum_{k=0}^D O(n, l-k) W^{(2)}(m, n, k) \quad (6)$$

where the details of incoherent detection or coherent detection followed by band pass filtering have been suppressed for simplicity. This final output is given by the thresholded outputs $P = f(p)$ and shows that this optical architecture can compute the same processing operation as a conventional TDNN.

4 Discussion

Typical AODs have time bandwidth products in excess of 1000, allowing up to 1000 neurons per layer to be implemented. This optical architecture can utilize video rate CCDs with on the order of 500×500

pixels and a 15.75KHz TDI shift rate. The resulting computational throughput exceeds 2 TFLOP.

Numerous demonstrations of holographic storage of well in excess of 1000 images have been accomplished, with diffraction efficiencies of each hologram on the order of 10^{-5} , but in the processor presented here all of these holograms are read out in parallel with the outputs summed. Additional summation in the TDI dimension serves to further accumulate photogenerated charge and to substantially reduce spatial nonuniformities. The optical power requirements to fully utilize the dynamic range of the CCD pixels assuming AO diffraction efficiencies of 10% is about 250mW. This is readily achieved in CW lasers, but the pulsed laser illuminating the second stage must be Q-switched and not a CW laser gated into a pulse.

Learning can not be readily implemented optically in such an architecture, but instead must be precomputed offline using appropriate training sets and then the resulting weights must be downloaded through an appropriate pixel matched multiple exposure holographic storage system. This has the disadvantage of not being self-aligning nor does it compensate for inevitable imperfections of the optical devices, but it allows sophisticated constrained training to be implemented digitally, and it utilizes the well developed holographic storage technology. The simple electronic inputs and outputs, the massive computational throughput, the efficient matching to existing technology, and the capability for applying sophisticated TDNN pattern recognition techniques at radar frequencies are the primary motivations for the proposed architecture.

References

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