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LMS TO DEEP LEARNING: HOW DSP ANALYSIS ADDS DEPTH TO LEARNING

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Outline

- Motivation
- Pulse Amplitude Modulation
- Demodulator Architecture
- Neural Network Topology & Training
- Simulation Results
- Conclusions

Motivations

- Since its inception, the LMS technique has been tied to learning systems (ADALINE = ADAptive Linear Neuron*)
- LMS has been extended to nonlinear neural networks and deep learning systems through the backpropagation algorithm
- Analysis and understanding are still catching up
- For communications, simple demodulators provide a useful frame of reference for evaluating learning techniques
- Our goal in this paper was a fundamental starting point similar to communication textbooks

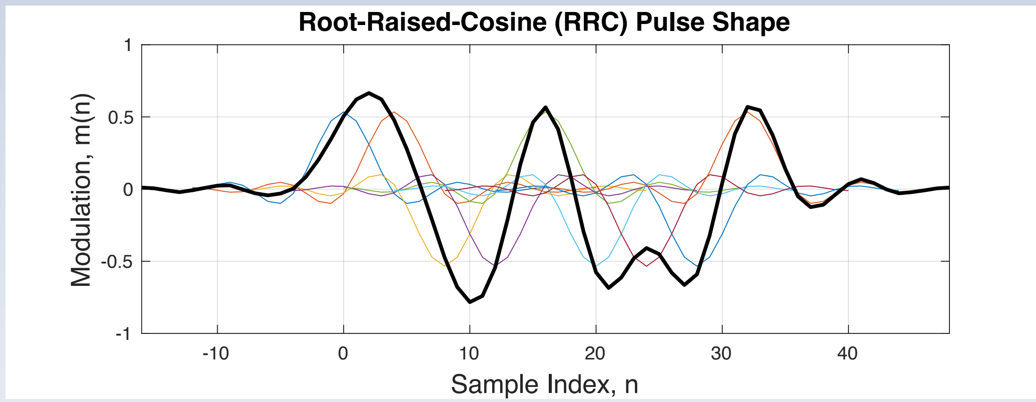
* B. Widrow, "Thinking about Thinking: The Discovery of the LMS Algorithm," IEEE Signal Processing Magazine, Jan. 2005

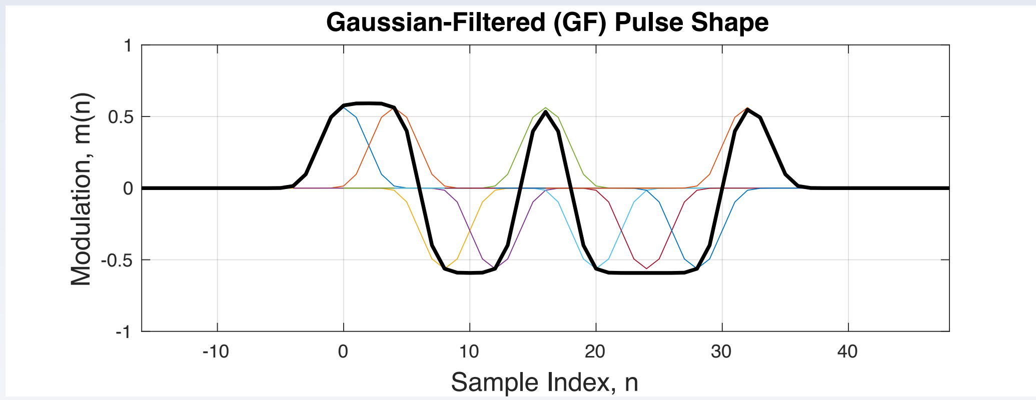
Pulse Amplitude Modulation

- Starting point for developing maximum a posteriori (MAP) and maximum likelihood (ML) classification strategies in most communications textbooks

$$m(n) = \sum_{k} d_k p(n - kT)$$

Data Pulse shape





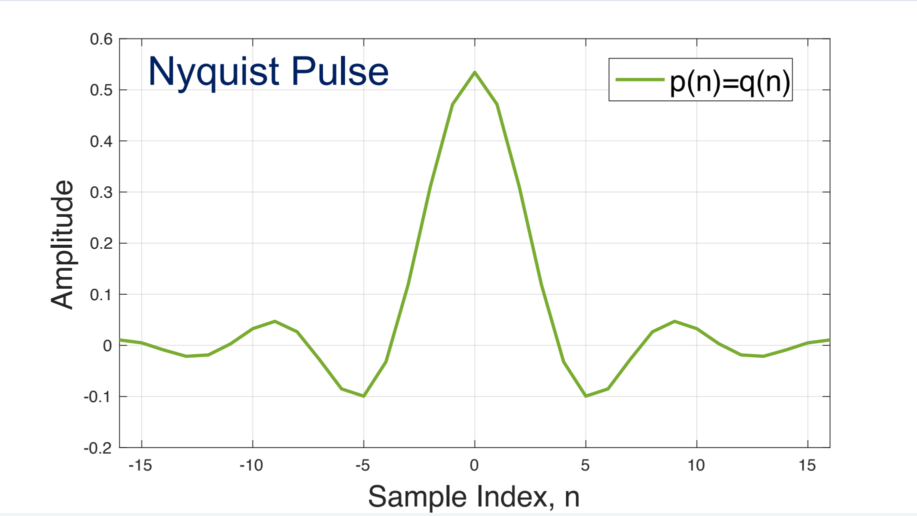
- Nyquist pulse shapes (Root-Raised Cosine) → orthonormal basis expansion
- Gaussian filtered pulse → non-orthogonal basis expansion

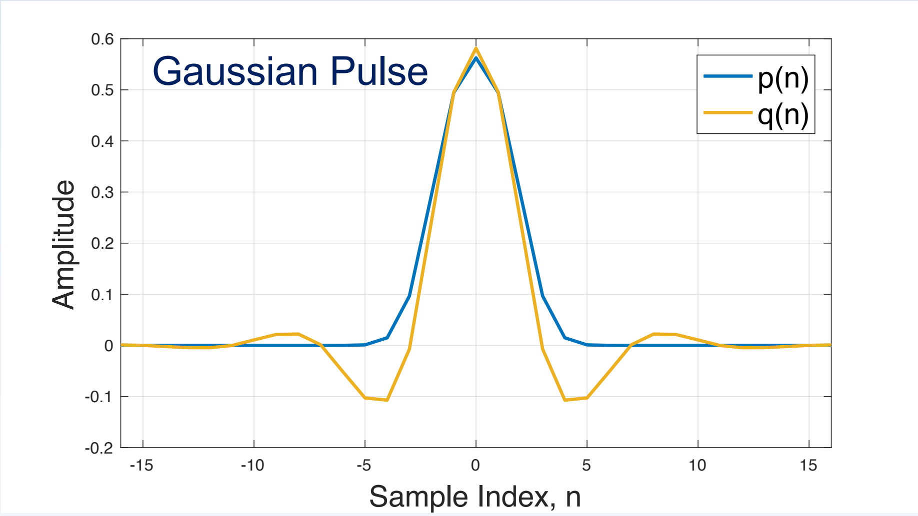
Demodulation

Data can be recovered using basis analysis equations

$$m(n) = \sum_k d_k p(n - kT) \qquad d_k = \sum_n m(n) q(n - kT)$$

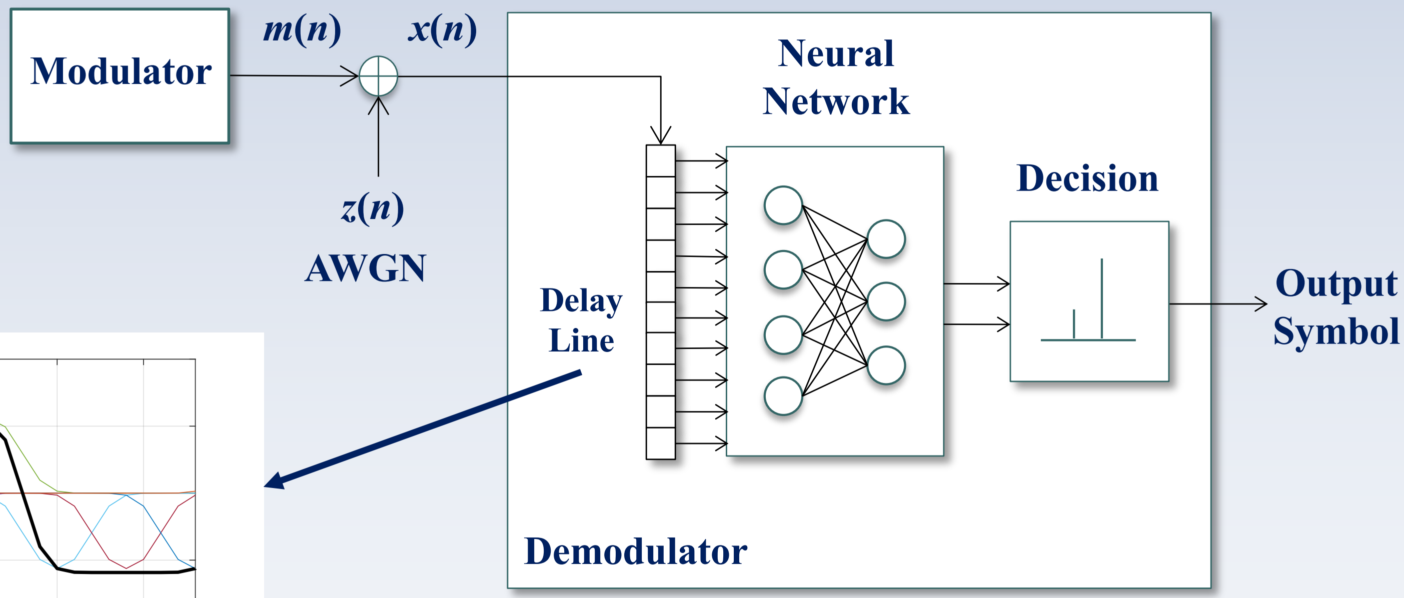
→ $\{p(n\text{-}kT)\}$ and $\{q\,(n\text{-}kT)\}$ must be biorthogonal sets



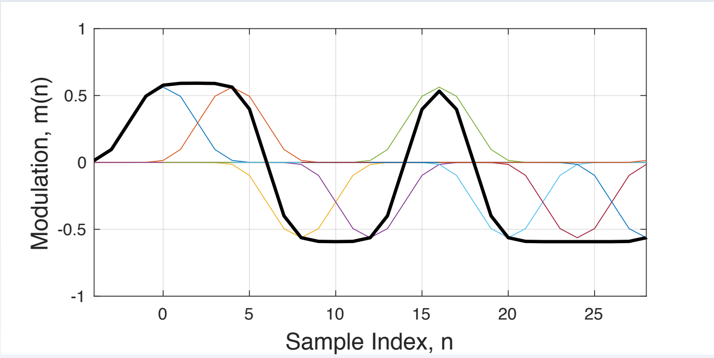


Demodulator Architecture

- Present synchronized instances of the received signal to a neural network for classification



Delay line contents

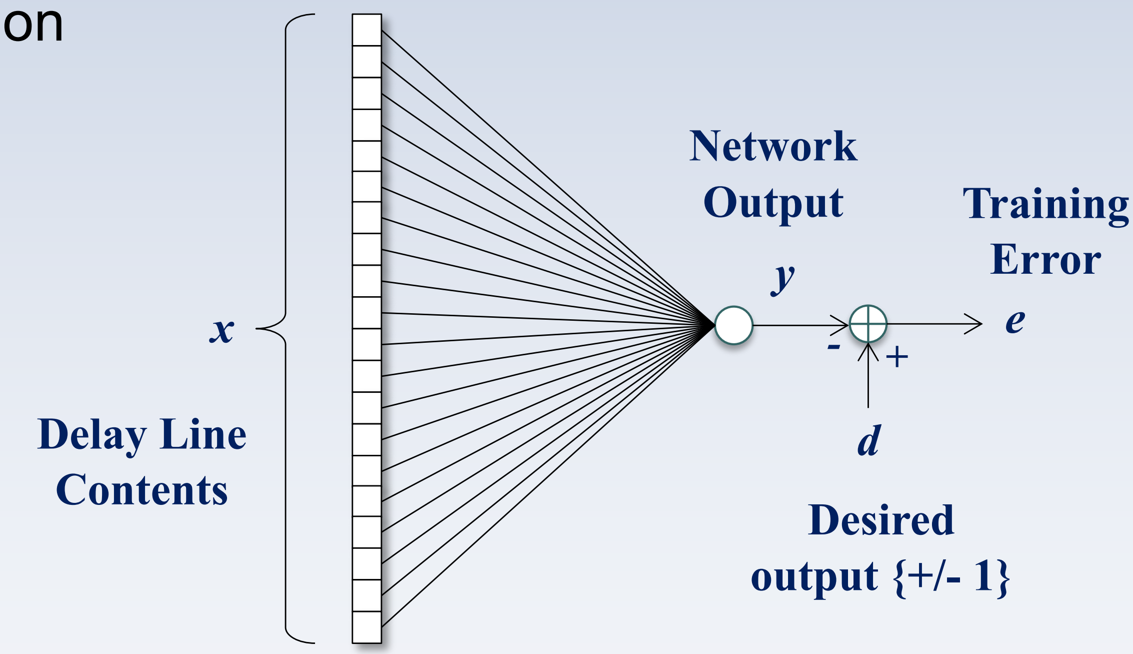


Neural Network Training

- Supervised learning with backpropagation
- Cost function is mean-squared error
- Neural network outputs interpreted as posterior probabilities
- Batch-mode stochastic gradient descent (SGD)
  - 1000 instances per batch
  - 2,000 epochs
  - Learning rate, $\eta = 0.1$
  - Training data included noise (E_b/N_0 = 7 dB, SER~0.001)

Elementary Feed-Forward Neural Network

- Single neuron with *tanh* activation function
- Nonlinear version of matched filter (correlation detector)



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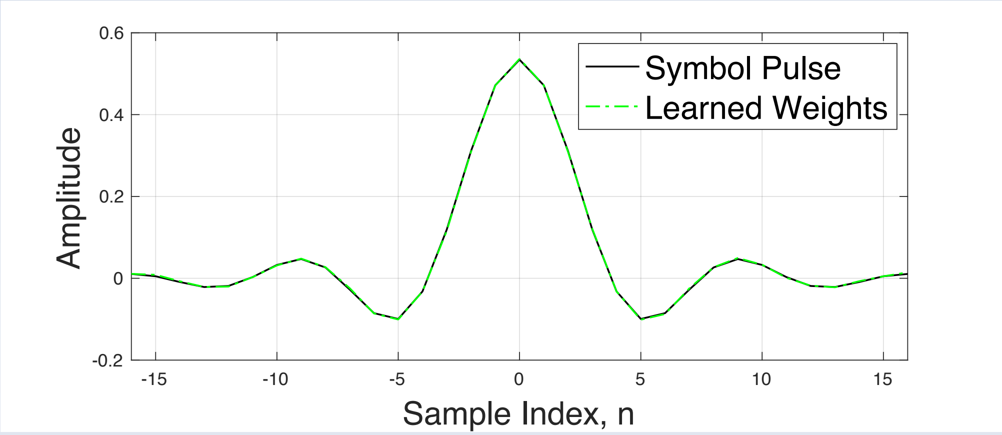
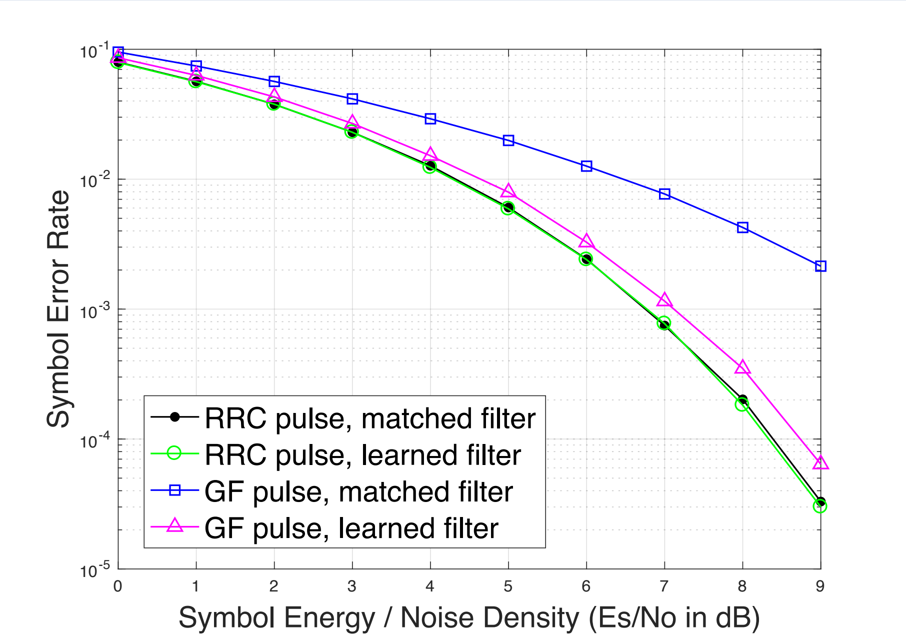
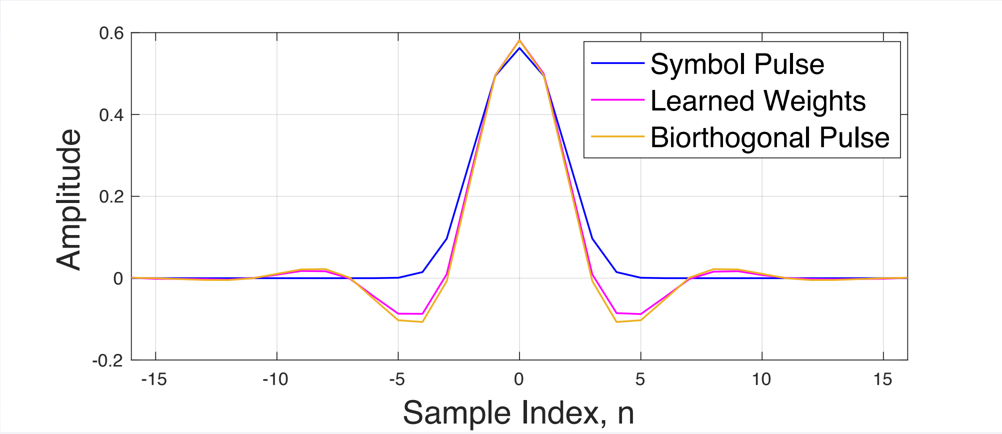
Results – Feed-Forward Network

- Nyquist pulse shape: FFNN learned orthogonal (matched filter) weights
- Gaussian-filtered pulse: network learned biorthogonal weights

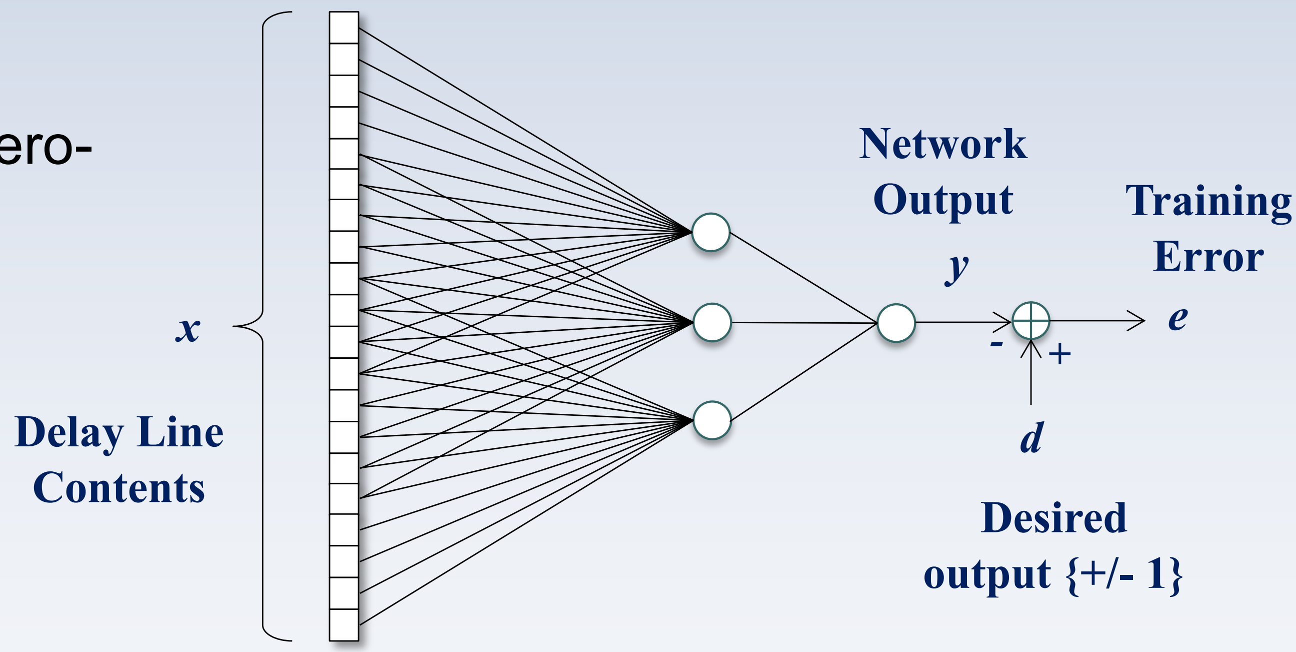






Elementary Convolutional Neural Network

- Three-node convolutional layer with stride equal to symbol spacing
- All neurons use *tanh* activation function
- Nonlinear version of matched filter plus zero-forcing equalizer



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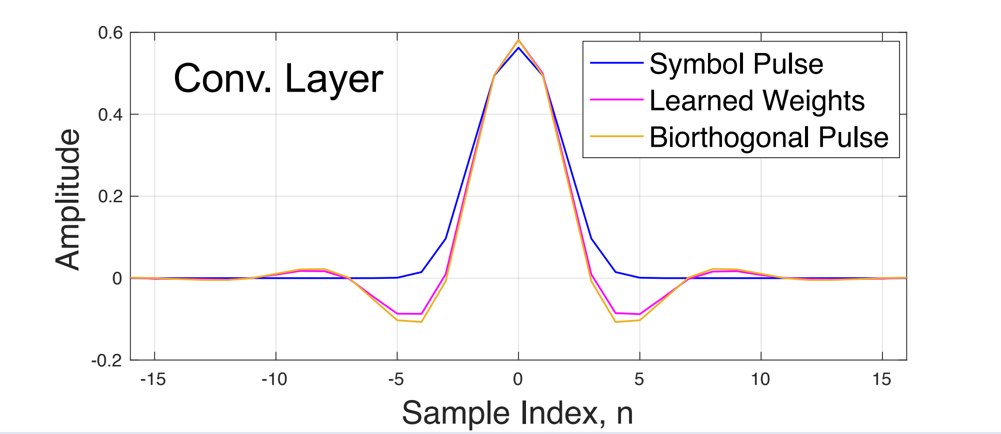
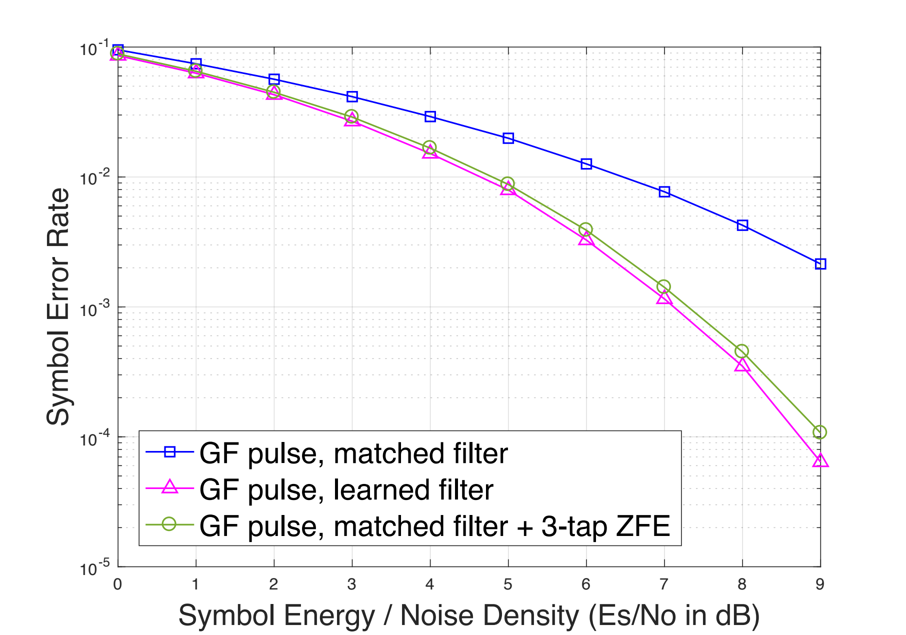
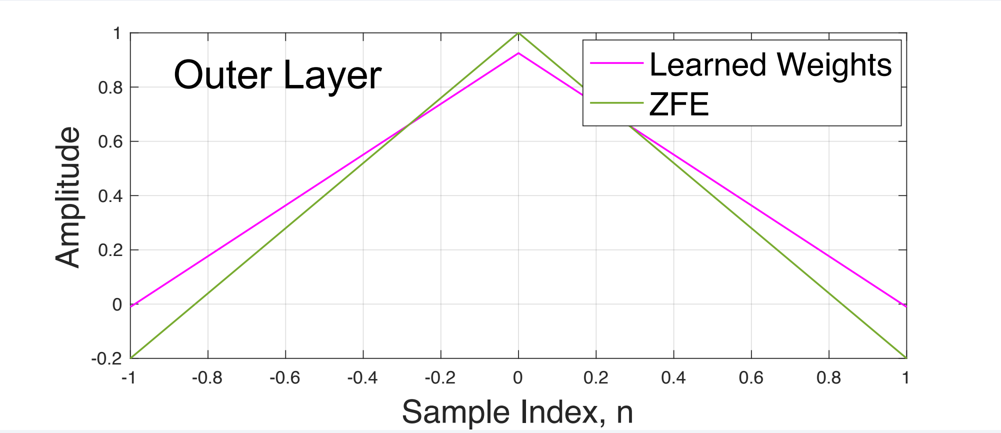
Results – Convolutional Network

- Gaussian-filtered pulse: CNN learned same solution as FFNN
- Performs slightly better than matched filter plus ZF equalizer



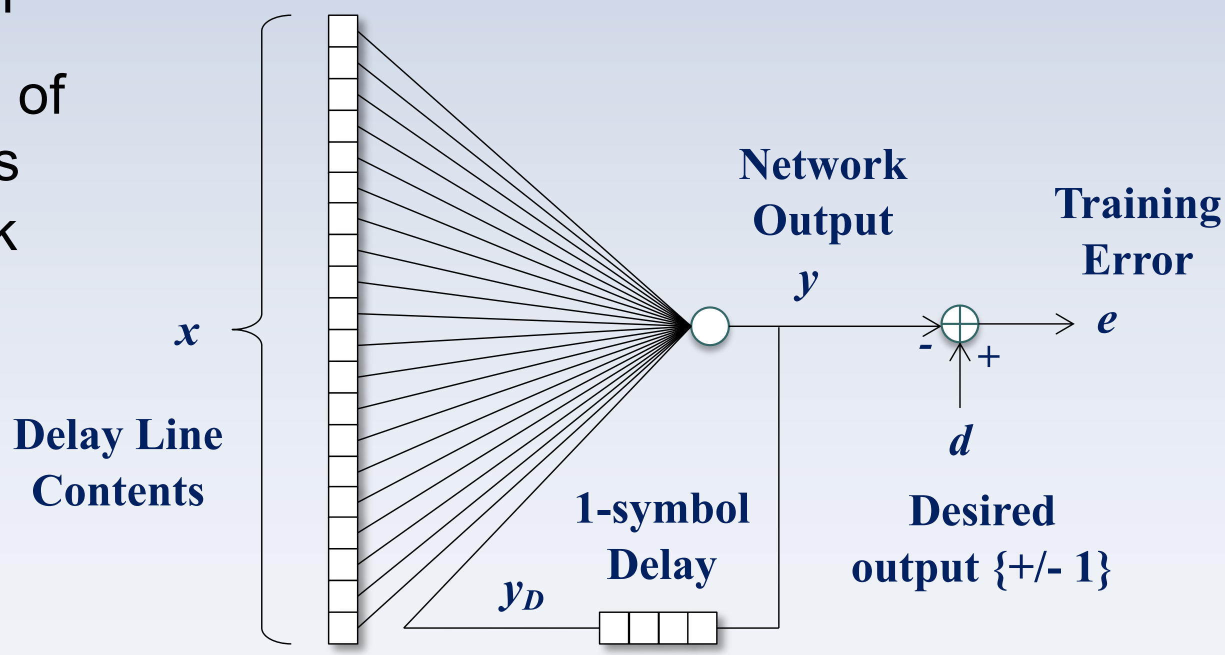




Flexible FSK Learning Demodulator

Elementary Recurrent Neural Network

- Feed back previous soft symbol decision
- Single neuron uses *tanh* activation function
- Nonlinear version of matched filter plus decision-feedback equalizer



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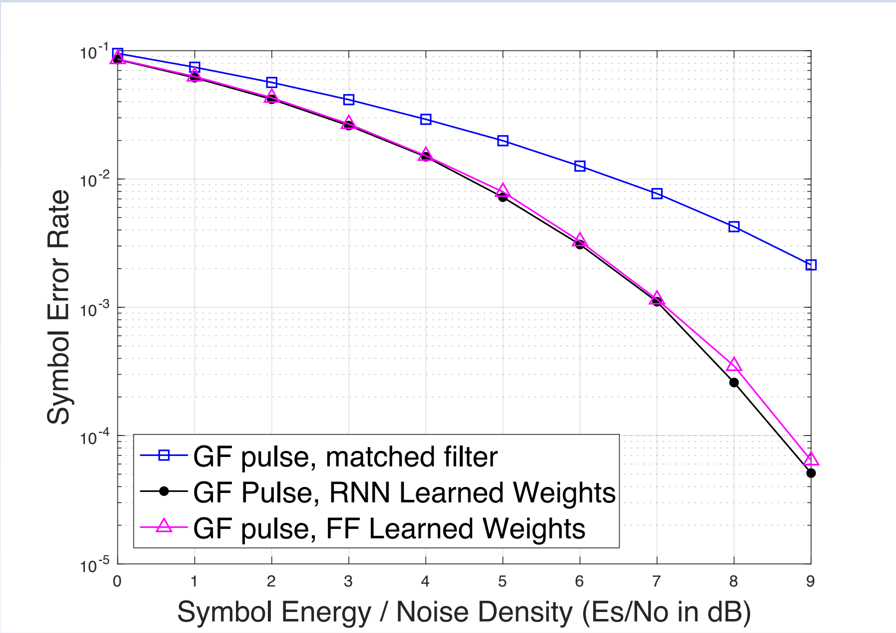
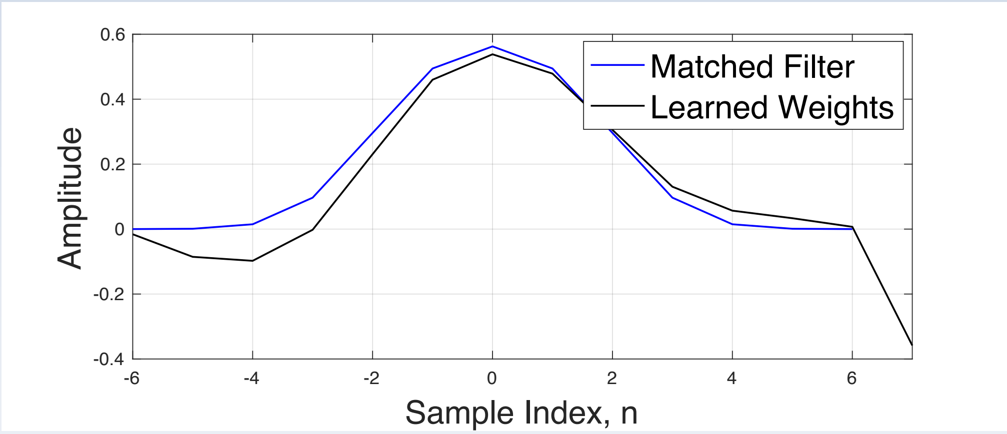
Results – Recurrent Network

- Gaussian-filtered pulse: RNN learned matched filter shape near the feedback symbol, biorthogonal shape where no symbol information is available
- Performed slightly better than CNN and FFNN





Conclusions

- Communications: Elementary neural networks learned matched filter or simple equalizer solutions
- Signal processing: Training process drives system toward orthogonal/biorthogonal solution
- Data driven: Signal-to-noise level during training affects balance between noise and orthogonality
- Activation: *tanh* served mainly to dampen learning rate
- Cost function: MSE focuses on signal quality, cross-entropy focuses on decision probabilities (equivalent in this simple case)