<u>CSCI 4366/6366 – Neural Networks & Deep Learning</u>

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Dept. of Computer Science
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Semester Project Template[1]

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[1] Template derived from Bock, P. (2001) Getting it Right: R&D Methods for Science and Engineering, Academic Press

1 Analysis

Digital Signal Processing (DSP) plays a crucial role in modern communication systems, enabling the efficient transmission and reception of signals. DSP techniques allow signals to be filtered, modulated, and demodulated while mitigating noise and interference. A key component of this process is filtering, particularly the design of matched filters that maximize signal-to-noise ratio (SNR) and ensure reliable data transmission.

A typical baseband digital communication system follows a structured process. First, source data is converted into a digital bit stream and mapped onto a carrier wave using a modulation scheme such as binary phase-shift keying (BPSK) or quadrature amplitude modulation (QAM). To control bandwidth usage and minimize inter-symbol interference (ISI), the modulated signal undergoes pulse shaping using a filter like a raised cosine filter. Once transmitted over a communication channel, the signal is received and processed using a matched filter that correlates with the transmitted pulse shape, maximizing SNR before demodulation and data recovery. To provide more context, the following diagram provides two implementations of a communication system: the upper graph illustrates the analog and RF-based process involving digital-to-analog and analog-to-digital conversions, while the lower graph represents the same process entirely within the digital domain.

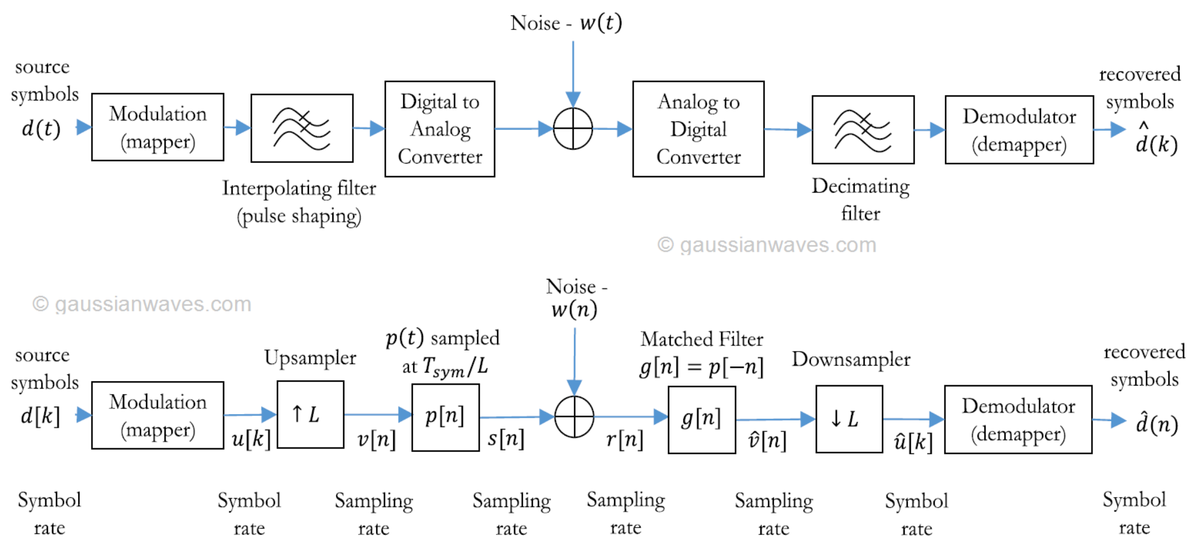

Figure - Analog/RF (top) and Digital (bottom) Communication System.

For optimal performance, both the transmitter and receiver must use the same pulse shaping function. If the receiver does not have prior knowledge of this function, its ability to accurately detect and decode signals is compromised. This can occur in cases where commercial hardware uses proprietary filters, real-world distortions modify the transmitted waveform, or intercepted signals require adaptive processing. Without an accurate matched filter, bit error rates increase, resulting in the deterioration of communication performance.

Thus, this project proposes using deep learning to enable a receiver to "learn" the pulse shaping function without prior knowledge. A deep learning architecture will be trained to infer the optimal finite impulse response (FIR) filter taps that maximize SNR. By learning from received signals, the model can hopefully generalize across different scenarios and adapt to unknown pulse shaping functions. To the best of my knowledge, no prior research has directly applied deep learning to estimate pulse shaping filters for matched filtering. While machine learning has been used in similar matched filtering topics, this project takes a novel approach by focusing on learning pulse shaping filters to improve matched filtering.

1.1 Problem Description:

DSP is essential for modern communication, enabling reliable transmission across WiFi, cellular, and RF networks. A crucial aspect of DSP is matched filtering, which maximizes SNR at the receiver. However, when the pulse shaping function is unknown, traditional matched filters fail, leading to increased bit error rates and degraded communication quality. This project explores whether deep learning can enable a receiver to learn the optimal matched filter by determining FIR filter taps directly from received signals.

Problem Description: Can deep learning be used to learn matched filters for pulse shaping in digital communication systems by maximizing SNR and learning the filter taps?

1.2 Performance Criteria:

- **Filter Estimation:** The model should accurately estimate FIR filter taps for randomly generated pulse shaping functions of varying lengths, with the inclusion of a few well-known ones like RRC.
- **Modulation:** The model should generalize to commonly used digital modulation schemes, mainly including BPSK, QPSK, 8PSK, and 16-QAM.
- **Noise:** The model should demonstrate robustness to varying channel conditions by incorporating different, potentially random, levels of Additive White Gaussian Noise (AWGN) and fading effects, such as Rayleigh fading.
- **Samples-Per-Symbol (SPS):** The model should generalize across different SPS rates.

- **Bit Stream:** The model should effectively reconstruct signals for arbitrary bit streams.

1.3 Related Work:

Matched filtering is a fundamental technique in signal processing, providing an optimal way of detecting known signals in the presence of noise. To give more context to the domain of this project, Turin (1976) [6], among many others, provides an introduction to digital matched filters, highlighting their role in maximizing the SNR and their widespread application in almost all communication systems. Additionally, Gentile (2007) [3] covers the principles of digital pulse-shaping filters, highlighting their importance in defining the transmitted signal's bandwidth and power efficiency, as pulse-shaping filters play a crucial role in mitigating ISI and optimizing spectrum efficiency in digital communication systems.

The application of machine learning to problems in the field of DSP is a relatively new and evolving area. While there has been no direct research on applying ML to learn matched filters for pulse shaping, several studies explore related applications. Broadly related to this paper's objective, the Universal Approximation Theorem, as discussed by Lu & Lu (2020) [5], demonstrates that deep neural networks can approximate arbitrary continuous functions, implying their potential for the domain of DSP. The theorem states that a sufficiently large neural network with at least one hidden layer and a non-linear activation function can approximate any continuous function on a bounded domain to any accuracy. More related to the domain of DSP, Yan et al. (2022) [7] present a generalized approach to matched filtering using neural networks, in which they leverage deep learning to replace traditional filtering techniques. Their work highlights that a neural network that can be analytically constructed to replicate matched filtering and further trained to enhance performance. Their study introduces two neural network architectures that implement matched filtering at initialization and can adapt to varying signals through training. However, Lu & Lu's and Yan's work do not directly address the problem of learning matched filters for pulse shaping in digital communication systems.

Still, several studies have investigated deep learning approaches for matched filtering in more specific domains. Dakic et al. (2023) [1] propose HybNet, a hybrid deep learning and matched filtering method for Internet of Things (IoT) signal detection, which integrates neural networks to enhance detection performance. Additionally, Gabbard et al. (2018) [2] explore the use of deep networks in gravitational wave astronomy, showing that neural networks can effectively mimic matched filtering methods for detecting gravitational wave signals. These studies highlight the growing interest in combining deep learning with traditional matched filtering techniques to improve performance and efficiency. However, the subject of focus in these studies differs from that of digital communication systems.

More related to the purpose of this project, Hu et al. (2024) [4] propose a deep learning-based approach for pulse-shaping filter estimation in fine-grained WiFi sensing. This study highlights the challenge of estimating unknown pulse-shaping filters and demonstrates the potential of deep learning in extracting filter characteristics from wireless signals. Their approach leverages channel state information (CSI), which encodes multiple-path propagation effects, to enhance pulse-shaping filter estimation accuracy. However, their research primarily focuses on estimating pulse-shaping filters for WiFi environments, without directly addressing broader digital communication scenarios. In contrast, this project aims to extend deep learning-based matched filter learning beyond WiFi sensing, optimizing SNR while hopefully generalizing across various modulation schemes, channel conditions, and bit streams.

1.4 Project Objective:

The objective of this project is to develop a deep learning model, leveraging convolutional neural networks (CNNs), long short-term memory (LSTMs), and potentially Transformers to learn matched filters for pulse shaping in digital communication systems. The model will aim to jointly maximize SNR and minimize the mean squared error (MSE) as its loss function to accurately estimate the FIR filter tap coefficients, while generalizing across various modulation schemes, bit streams, SPS rates, and channel conditions.

2 Hypothesis

Method: For the purpose of this project, two separate architectures, CNN and LSTM, will be explored for learning matched filters for pulse shaping in digital communication systems, with an emphasis on CNNs. Both methods will take IQ (In-phase and Quadrature) data as their input, where each time step represents a pair of real (I) and imaginary (Q) components of the signal. In the case of the CNN architecture, CNN layers are personally considered an intuitive approach due to the conceptual overlap. By applying convolutional layers to the IQ data, the CNN architecture can capture short-term features, potentially identifying shifts in signal composition and generating promising results. CNNs are especially powerful in handling spatial relationships and may work well for capturing localized features that may signify a pulse shaping function within signal sequences. The LSTM architecture is chosen due to its suitability for sequential data like IQ signals. LSTMs are capable of learning long-range dependencies over time and are specifically selected for their ability to handle sequences of arbitrary length, which is essential for simulating transmitted signals of varying lengths. This allows the model to capture temporal dependencies that may inherently exist within the IQ data that may be important for learning matched filters.

Data: All data for this project will be self-synthesized. The synthesis will follow the structure of a digital communication system. Initially, a random bitstream will be generated, which will be modulated using a randomly selected modulation scheme, such as QPSK or BPSK. This modulated signal will then be passed through a random pulse shaping function represented by its FIR filter taps given a randomly selected sps rate, creating a discretely sampled time-domain waveform. Afterward, noise will be introduced to simulate transmission over a non-ideal channel. The IQ data, representing the real and imaginary parts of the signal, will be the input to the model for processing. The dataset will consist of arbitrary random signals, each with the associated features: bitstream, modulation type, pulse-shaping function, SPS rate, and noise conditions.

Experiment: The performance of the model will be evaluated based on its ability to jointly maximize the SNR and minimize the MSE in its predictions of the FIR filter taps. The experiment will involve training the models on a dataset of IQ sequences, with corresponding FIR filter tap targets. The evaluation will focus on a custom loss function, defined by: the SNR of the predicted filter output compared to the original signal and the MSE between the predicted and actual filter taps. Additionally, the model's generalization ability will be assessed by testing its performance under various conditions, such as different modulation schemes (e.g., BPSK, QPSK), varying bitstreams, and different noise conditions, and SPS rates.

3 Synthesis

4 Validation

4.1 Results:

4.2 Conclusions:

Formal Conclusions:

Informal Observations:

Future Work:

5 References

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