Combining Deep Learning and Linear Processing for Modulation Classification and Symbol Decoding

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Abstract—Deep learning has been recently applied to many problems in wireless communications including modulation classification and symbol decoding. Many of the existing end-to-end learning approaches demonstrated robustness to signal distortions like frequency and timing errors, and outperformed classical signal processing techniques with sufficient training. However, deep learning approaches typically require hundreds of thousands of floating point operations for inference, which is orders of magnitude higher than classical signal processing approaches and thus do not scale well for long sequences. Additionally, they typically operate as a black box and without insight on how their final output was obtained, they can’t be integrated with existing approaches. In this paper, we propose a novel neural network architecture that combines deep learning with linear signal processing typically done at the receiver to realize joint modulation classification and symbol recovery. The proposed method estimates signal parameters by learning and corrects signal distortions like carrier frequency offset and multipath fading by linear processing. Using this hybrid approach, we leverage the power of deep learning while retaining the efficiency of conventional receiver processing techniques for long sequences. The proposed hybrid approach provides good accuracy in signal distortion estimation leading to promising results in terms of symbol error rate. For modulation classification accuracy, it outperforms many state of the art deep learning networks.

Index Terms—automatic modulation classification, blind symbol decoding, deep learning

I. INTRODUCTION

Recently, deep learning was proposed to address many problems in wireless communications [1]. Deep learning has been used for identifying signal modulation [2]–[5], estimating channels, and even building end-to-end communications [1]. Deep learning approaches can be used to solve many problems where training data can be obtained and practical modeling based solutions are not tractable like automatic modulation classification and blind symbol decoding.

Automatic modulation classification (AMC) is the problem of identifying the received signal type among a given set of modulations. Once, the modulation type has been recognized, blind symbol decoding aims to recover the transmitted symbols. These problems have many military and civilian applications. Military applications would use AMC for the interception of hostile communications while in civilian applications AMC could facilitate communications between cooperating radios without prior agreement or for adaptive communications.

In the deep learning literature, modulation classification and symbol recovery have been addressed separately. For modulation classification, many neural network architectures have been proposed and compared [2]–[5]. Even though neural networks for modulation classification learn to be robust to distortions like noise and carrier frequency offset, the black box nature of deep learning does not enable the extraction of the necessary information for signal reconstruction. Some of the existing works have proposed using signal processing inspired layers to improve modulation classification [6]–[8], while others have used a dedicated network to estimate the distortions [9]. But, none has proposed an efficient solution for both modulation classification and symbol recovery. Deep learning was also considered for decoding symbols of known signal types. Recurrent neural networks were proposed to decode received symbols in an unknown communication channel [10]. In [11], OFDM symbols were detected using neural networks. These approaches require a large number of FLOPS compared to classical approaches and are designed under the assumption of a known transmitted signal type.

Works leveraging signal processing techniques have considered blind joint symbol recovery and modulation classification. However, they often make many simplifying assumptions, e.g., known frequency and timing offsets or channel [12]. In [13], a decision tree algorithm based on statistical tests for blind modulation classification and symbol recovery was proposed. Joint blind channel estimation, modulation classification, channel coding recognition, and data detection using an iterative algorithm was considered in [14]. One of the disadvantages of signal processing approaches is that they require a large number of samples for parameter estimation and modulation classification.

In this work, we propose a deep learning approach combined with receiver signal processing for joint modulation classification and symbol recovery. The proposed approach consists of two paths: a feature path based on neural networks and a signal path using linear operations like filters. We refer to our approach as the Dual Path Network (DPN). Both paths are connected by neural networks extracting features from the signal path and providing the parameters to the signal path. The network incrementally reconstructs the signal and reuses it for a better estimation of parameters. The neural networks

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feature estimation and modulation classification require a very short sequence of input signal samples. The correction of input signal based on these parameters and decoding is performed using the linear signal path which can be applied efficiently on very long sequences.

The rest of the paper is organized as follows. The system model and the problem formulation are introduced in Section II. The proposed Dual Path network is described in Section III. In Section IV, we discuss datasets used in training and testing. The results are shown in Section V. Section VI concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A transmitter sends a vector of complex symbols \( s \in \mathbb{C}^N \) using modulation type \( M \) from a set of modulations \( \mathcal{M} \). In the most general case, the transmitted signal \( x(t) \) is determined by symbols \( s \) and symbol duration \( \tau \) through a modulation specific mapping function \( \mathcal{G} \) such that \( x(t) = \mathcal{G}(s, \tau) \). For a linear modulation type, the individual symbols \( s_i \) represent a mapping from bits to a predefined constellation point, and the transmitted signal \( x(t) \) given by \( x(t) = \sum_{k \in \mathcal{N}_s} s_i p(t - i\tau) \) where \( p(t) \) is the pulse shaping filter. The signal is upconverted and transmitted over a multipath fading channel modeled with an impulse response \( h(t) \). The downconverted and sampled received signal is modeled as the vector \( y \in \mathbb{C}^N \)

\[
y[k] = e^{j2\pi (f_0 k + \phi_0)} \int_{-\infty}^{\infty} x(\sigma) h(t_k - \sigma) d\sigma + n(t_k)
\]

where \( f_0 \) is the carrier frequency offset, \( \phi_0 \) the phase offset, and \( n(t) \) is the additive white Gaussian noise. We assume the receiver sampling rate \( \tau_0 \). Due to the sampling rate offset the sampling time \( t_k \) is given by \( t_0 + k\tau_0 \), where \( \tau_0 \geq \tau \) and \( t_0 \) the sampling phase offset such that \( 0 \leq t_0 \leq \tau_0/2 \). The length of transmitted and received symbols is related as \( N_s = \left\lceil \frac{\tau_0}{\tau} \right\rceil \).

Given vector \( y \), the receiver’s objective is to identify the modulation type \( M \) and recover the transmitted symbols \( s \). The signal identification should be accurate using short sequences and the recovery scalable to long sequences in a computationally efficient manner.

III. DUAL PATH NETWORK (DPN)

The proposed network architecture is inspired by the signal demodulation flow used in conventional digital demodulators when the modulation type, pulse shape, symbol rate, and carrier frequency are known a priori. Any residual errors are estimated and corrected one after the other [15]. The compensation of these errors is typically done using linear operations like filters. Due to the lack of knowledge about the transmitted signal parameters we explore deep learning for parameter estimation.

The proposed network consists of two paths: a signal path consisting of linear operations inspired by existing signal processing methods, and a feature path where deep neural networks (NN) learn different signal parameters. The overall network is shown in Fig. 1. Both paths are connected using a set of neural networks. Feature extractor NNs process the signal to learn features. Parameter estimator NNs use the learned features to estimate the parameters and feed them to the signal path for correction and reconstruction of the signal. As in a typical demodulation flow, the signal reconstruction and parameter estimation are done incrementally. We start with noise estimation and reduction, followed by correction of frequency offset, matched filtering and equalization. Using this incremental approach, each stage benefits from the correction performed by the previous stage.

A. Architecture

The network takes one input, which is the received samples \( y \), and generates five outputs (op) as shown in Table I. An example for a BPSK signal is shown in Fig. 1. The first three outputs are processed signals with distortions correction, namely noise reduction, carrier frequency offset correction, and equalization. The fourth output estimates the timing errors and specifies the ideal sampling time. The function \( g(t) \) generates a binary vector with the same length as the signal having transitions at the sampling time as shown in the timing plot in Fig. 1. The last output \( z_0 \) is the one-hot encoding given by the function \( g_m \) of the modulation type.

The neural network (NN) structure of each block is shown in Fig. 2. The entire network consists of a combination of residual blocks and recurrent neural networks. The “Matched Filter” (MF) Equalization Filter Estimator” is similar to the “Noise Filter Estimation” block except that the former has 65 filter taps and the latter 64. The “Timing NN” is made of two LSTMs, where the internal state of the first one is fed to the following LSTM, which takes zeros as input, followed by a time distributed dense network with sigmoid activation. As for the signal path, the “Noise reduction” and ”Equalization & MF” are implemented as linear filters performing convolution based on estimated filter taps. The ”Frequency Correction” performs complex multiplication with a complex exponential using the estimated frequency offset.

As stated, the signal path consists exclusively of linear operations. While this design choice sacrifices the ability to correct for nonlinear distortions, it brings many benefits; first, for long sequences, once the modulation type, timing information, frequency offset, and filter taps have been estimated, there is no need to keep inferring them using the neural network. Typically neural networks used in signal processing consist of hundreds of thousands of parameters, and inference requiring hundreds of thousands of floating point operations. Using this design, the inferred parameters can be reused and applied to very long sequences using simple operations. Second, the estimated parameters are interpretable and compatible with existing signal processing approaches. For example, if the frequency offset is variable during the signal duration, a phase locked loop can be used to track it.

B. Training

Typically neural networks rely on non-linear operations between layers for training. Since the signal path is designed to have linear operations, the signal outputs (op1, op2, op3)
are necessary for each stage to perform its task. Additionally, gradients are prevented from backpropagating into the signal processing blocks from the following layer since the desired output is already provided. During training, an additive white Gaussian noise is added to the signal before the "Equalization & MF" stage to improve its training in the high SNR regime. Since this network has multiple outputs, the training loss is a combination of different losses shown in Table II. \( \hat{z}_i \) is the network output for \( z_i \). For op1, to reduce the noise, we use the mean squared error loss. For op2, we use a loss function that does not penalize constant phase shift.

**Fig. 1:** The Dual Path network consists of feature path and a linear signal path connected using neural networks (NN) for parameter estimation and feature extraction. An example input signal is shown along with the predictions in solid and the reference output in dashed. The output constellation is obtained by sampling \( \text{op3} \) using \( \text{op4} \).

**TABLE I: Output description**

| Name   | Description                        | Equation       |
|--------|------------------------------------|----------------|
| op1    | Noise removed \( z_1[k] = y[k] - n(t_0 + k\tau) \) |               |
| op2    | Frequency corrected \( z_2[k] = e^{-j\pi f_0 t_0 + k\tau} z_1[k] \) |               |
| op3    | Recovered Signal \( z_3[k] = x(t_0 + k\tau) \) |               |
| op4    | Timing information \( z_4[k] = g(x(t_0 + k\tau)) \) |               |
| op5    | Modulation type \( z_5 = g_m(M) \) |               |

**TABLE II: Loss Functions**

\[
L = \sum_{i=1}^{N} w_i L_i
\]

\[ L_1 = \frac{1}{2} ||z_1 - x_1||^2 \]

\[ L_2 = \frac{1}{2} (z_2^H \tilde{z}_2 + z_2^H z_2 - 2|z_2|^2) \]

\[ L_3 = \frac{1}{2} (S(z_3^H)S(z_3) + S(z_3^H)^2S(x_1) - 2|S(z_3)|^2S(x_1)) \]

\[ L_4 = \min \{L_{b_0}(x_2, x_1), L_{b_0}(1 - x_1, x_1) \} \]

\[ L_5 = L_{b_0}(x_5, z_5) \]
whether the transmitted signal was \( x \) and \( -x \) without side information, which is not available to the network. For op3, we use a phase insensitive loss based on the values at the sampling time instances. The vector function \( [S(x)]_i = x[i] \) if \( z_4[i] \neq z_4[i + 1] \), and zero otherwise, this samples the signal at the transitions of \( z_4 \). For the "Timing NN" output op4, we apply a vector binary crossentropy loss, such that \( L_{bn}(x, y) = \frac{1}{N} \sum_{i=0}^{N} L_{b}(x[i], y[i]) \) where \( L_b \) is the binary crossentropy loss. Since the information lies in the transition and not the values, we consider the minimum loss of \( z_4 \) and its inverse \( 1 - z_4 \). As for "Modulation Classification" NN, we use a categorical crossentropy loss \( L_c \). The total loss is a weighted combination of these losses with weight vector \( w \). The optimizer used for training is the ADAM optimizer with a learning rate of 0.001 and the gradients were clipped at a norm of 1.0.

IV. DATA GENERATION AND DATASETS

We generate datasets consisting of samples with different data, modulation types, symbol rates, timing and frequency offsets, phase, channel impulses, and SNRs. Each sample is generated according to the flow graph shown in Fig. 3. Random data \( d \) is generated and modulated using modulation type \( M \) selected from the set of modulation \( M \). If \( M \) is a linear modulation, the output is pulse shaped with a root-raised-cosine filter with a roll-off factor \( \beta \). The output is sampled with an offset \( t_0 \) and a sampling time \( \tau_0 \). Multipath fading is simulated using convolution with random fading taps having a delay spread \( \sigma \). Then frequency and phase offsets, \( f_0 \) and \( \phi_0 \), are applied, and Gaussian noise is added to model different SNRs.

All aforementioned signal parameters are chosen randomly from specified ranges. Two datasets are considered with \( N_r = 128 \) and each dataset is defined by the range of each parameter as given by Table III. Both datasets have \( \beta \in \{0.15, 0.35, .55\} \), \( t_0 \in \{0, \tau_0 / 2\} \), \( \phi_0 \in \{0, 2\pi\} \), \( h \) has 3 non zero taps having \( \sigma \in \{0.5r/\tau_0, 4r/\tau_0\} \) with the non-line-of-sight taps having average magnitudes of 0.5 and 0.1. Dataset 1 has fewer modulations and less severe distortions, while Dataset 2 is more challenging due to more modulation types, larger frequency offsets, and significantly different values of samples per symbols \( \tau_0/\tau \). Dataset 2 is used in the evaluation of the signal and symbol recovery.

Typically, a fixed dataset is used in training, and data augmentation is performed to avoid overfitting. Since our dataset is generated using simulation, instead of fixing the training data, we generate the samples in real-time during training. This means that each epoch consists of a new set of samples which effectively avoids overfitting. As for validation and testing, two fixed datasets are used with one million samples in each.

V. RESULTS

A. Modulation Classification

We evaluate the modulation classification performance of our proposed DPN and compare it to the state of the art approaches for modulation classification. Namely, we consider the ResNet architecture [2], the CLDNN architecture [3], the Stacked GRUs (SGRU) [4], and ICNet [5]. All these approaches use as input IQ samples and directly predict the modulation class without generating any other information about the signal. In terms of the number of parameters, DPN has 189K trainable parameter which is about the same number as the smallest network.

For Dataset 1, DPN was allowed up to 100 epochs, and for Dataset 2 DPN had up to 200 epochs. Since DPN has access to the intermediate stages of the signal, to be fair in comparison the remaining networks were allowed to have up to 4 times more data and training epochs than DPN. Each epoch consists of 800K samples and the batch size was adjusted for maximum GPU utilization. The network training was stopped if the validation loss did not improve for ten epochs. The results for Dataset 1 is shown in Fig. 4a and for Dataset 2 in Fig. 4b. From these figures, we see that DPN significantly outperforms most of the existing approaches except for the SGRU. The SGRU performs close to DPN but does not provide symbol decoding. Hence, DPN performs as good or better than the state of the art approaches in modulation classification.

The performance on Dataset 2 does not exceed 65% for any of the approaches due to confusion in high ordermodulations. This can be explained by the fact that we consider high order modulations up to QAM 256 and with only up 16 samples per symbol there are only a few symbols in 128 samples.

To understand the significance of having the intermediate signals in DPN, we train several partial instances of DPN. In all these instances, the feature path is the same and we incrementally add the signal stages and the corresponding extractors and estimators. DPN 0 is obtained by removing the signal path and the timing module, hence, the network

| Param. | Dataset 1 | Dataset 2 |
|--------|-----------|-----------|
| \( M \) | \{ BPSK, QPSK, PSK8, QAM16, GMSK, CPEFSK, ASK4 \} | \{ OOK, ASK4, ASK8, BPSK, QPSK, PSK18, PSK16, PSK32, APSK16, APSK32, APSK64, APSK128, QAM16, QAM32, QAM128, QAM256, GMSK, CPFSK \} |
| \( f_0(Hz) \) | \( [0, 0.0025/\tau_0] \) | \( [0, 0.005/\tau_0] \) |
| SNR (dB) | \( [-20, 20] \) | \( [-10, 40] \) |
| \( \tau_0 / \tau \) | \( [7, 9] \) | \( [3, 16] \) |

TABLE III: Dataset Description

![Flow graph for generating samples showing on top the input parameters and the bottom the outputs used for training.](image-url)
is trained similar to the existing approaches. For DPN 1 we add the noise filtering stage. For DPN 2, we add the first two stages, and for DPN 3 we add all signal stages. Our original DPN contains all 3 signal stages and the timing module. Fig. 4c shows that each stage incrementally improves the performance of modulation classification.

B. Parameter Estimation

The performance of DPN in terms of parameter estimation is evaluated on the signals in the test set of Dataset 2 and the averaged results are shown in Fig. 5. Fig. 5a shows the SNR of the predicted signal $z_\hat{1}$ plotted against the SNR of the input signal $y$. We see that the noise reduction stage significantly increases the SNR for low SNR signals. For very high SNR signals, above 30 dB, the first stage seems to add small amounts of noise to the signal. However, for high SNRs, this loss does not have any significance for the symbol recovery.

To evaluate the improvement in frequency estimation, we calculate the ratio between the residual frequency offset after correction and before correction $\frac{E(f_0 - \hat{f}_0)}{E(f_0)}$ where $E$ is the mean calculated per SNR and $f_0$ is the estimated offset. This improvement is shown in Fig. 5b. We can see that for high SNR, the carrier frequency offset gets reduced to below 5%.

For symbol rate estimation, the average absolute error per SNR given by $\frac{E|\tau - \tau_0|}{\tau_0}$ is shown in Fig. 5c. Again, DPN achieves a low timing estimation error for SNR above 5dB. It is worth noting that these estimates are obtained from a very short signal consisting of 128 samples without knowing the signal type.

C. Symbol Recovery

We evaluate DPN’s ability to decode the symbols blindly. As a reference, we compare it to a signal processing based approach described later. In this evaluation, we focus on the symbol error rate, and to that end, for both approaches we make the following assumptions: (1) modulation type was inferred correctly and this is valid for low order modulations; (2) the sampling instances were accurately determined to make sure that the compared symbols are aligned; (3) the phase is accurately recovered to handle phase ambiguity. For both approaches, we only consider symbol recovery for linear modulations and use the conventional minimum Euclidean distance receiver.

Note that for many of the classical estimation approaches, a vector of length 128 is too short to derive an accurate estimate of the signal parameters. Therefore, as a reference signal processing approach, we assume a genie approach for the frequency recovery, and we consider a fixed low pass filter that works for all samples in the dataset. No channel equalization is performed in the DSP approach due to the short sequence and the lack of channel state information.

The results for the symbol error rates (SER) at different SNRs for PSK and QAM modulations are shown in Fig. 6a and Fig. 6b. We can see that at high SNR, DPN outperforms the DSP approach. We explain this result by the fact that DPN learns to perform blind equalization to the signal. At the lower SNRs, DPN frequency correction is not very good which leads to high SER.

D. Remarks on DPN Complexity and Scalability

One of the advantages of the Dual Path network is its ability to perform symbol recovery over long sequences efficiently. In contrast, fully NN based approaches would have to be applied over long sequences at a high computational cost. For an input of 128 samples, DPN consumes about 316 KFLOPS, out of which signal path only uses 33K FLOPS. That’s about 10 times less operations (without combining linear operations).

To evaluate the effect of reusing the estimated parameters on SER, we generate 1000 QPSK signals of lengths 512, 1024. These signals are divided into chunks of 128. We compare the SER results when DPN is applied on all chunks to the case when it is applied to the first chunk and then the signal path only uses the estimated parameters on the remaining chunks. The results in Fig. 7 show that there is no significant impact from reusing the parameters. Hence, we can get about a 10 times reduction in FLOPS to achieve the same SER for subsequent chunks.
VI. CONCLUSION

We have proposed the Dual Path Network for joint blind modulation classification and symbol recovery. By combining neural networks along with linear signal processing, we are able to leverage the power of deep learning for parameter estimation while retaining the efficiency of classical signal processing techniques for long sequences without sacrificing performance. Results show that DPN can estimate the signal parameters for SNRs above 5dB with a very low number of samples and that the performance of modulation classification surpasses many of the state of the art networks. The successful reconstruction enables blind symbol recovery with symbol error rates lower than a genie signal processing approach without equalization under high SNR. In our future work, we will consider increasing the number of samples used to improve the performance of modulation classification. We will also compare our approach with a fully blind classification approach for symbol recovery.

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