Simplifying Meta-Beamforming Algorithms for Massive Wireless Networks

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Abstract—**Machine learning in wireless communications has helped to solve many important issues related to next generation wireless systems. One major issue encountered by modern communication system is related to spatial multiplexing and reducing interference caused by neighboring users [13]. To reduce this interference, modern systems use electronic beamforming to direct the radiation pattern of each user away from every other user while maintaining contact with the base-station [2]. The optimal solution to this problem is an NP-hard Minimal Mean Squared Error (MMSE) optimization problem with a slow response time that needs to be recalculated as the users move and the channel properties changes [10]. To get around this, Deep Neural Networks (DNNs) have been deployed at various levels to either estimate the end-to-end problem, or to estimate certain difficult portions of the original computation [4]. This paper attempted to improve upon the architecture presented in [14] to reduce the computational complexity of calculating the optimal beam forming weights by using a GRU based architecture instead of an LSTM. While implementation details combined with an insufficiently documented source prevented further exploration, a great deal was learned about deploying neural networks in a reinforcement learning setting.**

I. Introduction

THE coming Industry 4.0 requires high-density wireless device connectivity with high-throughput [13]. High data-throughput requires large amounts of bandwidth, but bandwidth used by one device cannot be used by others. To mitigate this, traditional networks deploy time and frequency domain multiplexing [13]. These solutions allocate finite time and frequency between different users, and so through-put collapses as the number of users increases. To solve the problem of finite time and frequency, 5th generation networks apply spatial multiplexing which allows multiple users to share time and frequency and not interfere with each other [2], [13]. Spatial multiplexing is performed by electrically shaping the beam of an array of antennas toward its target and away from other users [2]. Beam-forming requires calculating weights and phase delays for a spatial array of antennas so that radiation goes mostly where desired and avoids undesired places [6], [4], [3].

The problem of optimizing antenna weights so that radiation reaches its target and avoids interfering with other users is NP-Hard [16]. Modern communications systems solve for the optimal weights using the Minimal Mean Squared Error method [16]. Because the MMSE method is iterative, the algorithm adapts slowly to changing environments which is unacceptable for mobile communications networks. To mitigate the slow response of the optimal solution, many sub-optimal approximations and other optimizations have been explored [12]. One optimization that shows promise is deploying Deep Neural Networks (DNNs) to approximate the antenna

weights in dense networks [4]. State of the art beam-forming networks deploy DNNs either in end-to-end configurations, or to approximate difficult portions of the MMSE algorithm [4].

The paper [14] implemented an LSTM to decrease the computation required to find optimal antenna weights. The authors of [14] used an LSTM network to learn how to optimize the parameters of the optimization problem in a method that will be discussed later in the paper. The method of using LSTMs is the state of the art method for finding optimal antenna weights [4], [14]. This paper attempted to reduce the computation required to find antenna weights further using a simpler recurrent architecture, the Gated Recurrent Unit GRU and to document the process of training this architecture. This remains open work since this project was unable to properly replicate results of [2], [4], [10], [14]. The remainder of this paper will discuss in detail the exact optimization method attempted in the background and prior work sections, the experimentation and model section will detail the model attempted, followed by the results that were achieved in pursuit of this project. Finally, a conclusion discusses possible future work.

A. Background

Using multiple antenna to electrically shape antenna beams has been a staple of advanced wireless communication and radar systems since around the 1970's [**?**]. Beamforming works by exploiting the additive properties of electro-magnetic waves which increase intensity when added in phase and can completely level a wave when added out of phase. Controlling the phase of multiple antenna, it is possible to control where in space the interference pattern from all the antenna's radiation patterns add constructively and where the interference adds destructively [**?**].

The ability of antenna systems to beamform depends primarily on the physical arrangement of the antenna in relation to their wavelength. Since early mobile communication systems used relatively long wavelengths, beamforming systems would need to be tens of centimeters at their smallest [**?**]. This was acceptable because the long wavelength used in early cellular communication systems suffered far less attenuation than the frequencies of 5th (and soon 6th) generation wireless systems [**?**]. Besides physical concerns related to antenna, it is mathematically difficult to calculate how to design the phase-delay and attenuation of each antenna in an array for a system involving even a few users [**?**].

An ideal multi-user beamforming system would be able to direct radiated energy at intended users while perfectly avoiding unintended users. The best known algorithm for finding parameters required to perform beamforming like this is

called the Weighted Minimal Mean Squared Error (WMMSE) method and was first published by [**?**]. Since the WMMSE algorithm was first introduced, it was recognized as lacking many desirable qualities and several attempts have been made to improve the algorithm. Of specific interest was [**?**] who reformulated the original optimization problem in a way that permitted unrolling.

B. WMMSE for Beamforming and System Model

The problem formulation for the WMMSE in this analysis is presented by [**?**]. The system model is a multiple-input single-output, additive interference downlink channel. The downlink base-station has M independent transmit antenna and sends data to N single antenna users. All signals are considered to be additive, and so the received signal at user i is given by Equation 1.

$$y_i = h_i^H v_i x_i + \sum_{j=1, j \neq i}^{N} (h_i^H v_j x_j) + n_i \qquad (1)$$

The terms from this base equation are defined as:
- h_i: is the ith column of the complex channel matrix, H
- v_i: the complex antenna beamforming vector for user i
- x_i: the intended symbol to be sent to user i
- n_i: the circular Gaussian complex noise at user i

Each of these values can be complex to capture the magnitude and phase effects each variable. From this, notice that the first expression in Equation 1 represents the intended symbol received by user i. The second term is the interference received by user i caused by the base-station transmitting to other users. Vectors v_i and h_i have matrices V and H where each row represents a user and each column an antenna at the base-station. This way, the model captures the intended configurable weights of all transmit antenna (M) to send messages to each user (N) with V and the effect of the channel from each transmit antenna to each user. From this, [**?**] presents a global loss function to minimize the anticipated error rate of the system shown in Equation 2.

$$\mathcal{L} = \min_{u,w,V} \sum_{i=1}^{N} \alpha_i (w_i e_i - log_2 w_i) \qquad (2)$$

Where e_i is the expectation of error quantified in Equation 3 as:

$$e_i = \mathbb{E}_{x, n_i}\{|\hat{x}_i - x_i|^2\} \qquad (3)$$

Lastly, $\hat{x}_i$ is given as:

$$\hat{x}_i = u_i y_i \qquad (4)$$

From these equations, the following new parameters are defined:
- α_i: A system design parameter describing importance of user i
- w_i: An optimized weight assigning importance to user i
- e_i: The expectation of error for user i
- u_i: User i's amplification

Looking deeper, w_i provides a way for the optimization algorithm to determine how important each node can be allowed to be, but prevents w_i from being too small. Furthermore, a receiver gain u_i is introduced. This parameter is controlled by users and allows each user to amplify received signals. The cost of doing so is increasing the amount of noise amplified by the receiver, so an optimization algorithm must find a way to balance that competing interest. Finally, there is also a weight α_i that can be assigned to each user by the system designer to describe how important each individual user is.

With the above equations, it is possible to define the fixed station update equation for each parameter as:

$$w_i = \frac{\sum_{j=1}^{N} |h_i^H v_j|^2 + \sigma^2}{\sum_{j=1, j \neq i}^{N} |h_i^H v_j|^2 + \sigma^2} \qquad (5)$$

$$u_i = \frac{|h_i^H v_i|^2}{\sum_{j=1}^{N} |h_i^H v_j|^2 + \sigma^2} \qquad (6)$$

$$v_i = \alpha_i u_i w_i h_i (A + \mu I)^{-1} \qquad (7)$$

Notice how the raw update function for v_i in Equation 7 has a matrix inversion of $(A + \mu I)$. This is overcome by [**?**] through the use of Projected Gradient Descent (PGD) using the Lagrange multiplier method. Applying the PGD method transforms the error for e_i function from Equation 3 to be 8.

$$e_i = \sum_{j=1}^{N} |u_i h_i^H v_j|^2 - 2u_i h_i^H v_i + \sigma^2 |u_i|^2 + 1 \qquad (8)$$

Next, the gradient of V is calculated explicitly as:

$$\nabla f(v_i) = -2\alpha_i w_i u_i h_i + 2A v_i \qquad (9)$$

Finally, A is a matrix given in Equation 10

$$A = \sum_{i=1}^{N} \alpha_i w_i |u_i|^2 h_i h_i^H \qquad (10)$$

The above equations were derived in more detail by [**?**] and the interested reader is directed there for additional details. The presented equations are necessary for understanding the problem statement and explaining the

This section will describe in detail the problem formulation which [**?**] used LSTMs to solve and which served as the basis of the work explored here and in [**?**]. The way the WMMSE algorithm works is to iteratively update each variable u_i, w_i, and V_i with the respective update functions shown in Equations 6, 5, and 7 respectively. The update procedure is repeated until an acceptable error is reached.

As was shown above, the original formulation for updating V_i involved a matrix inversion, so deep unfolding was implemented by [**?**] to circumvent the complications of calculating an inversion directly. Coincidentally, unfolding in this way creates a continuous path for gradients to flow within the entire problem which [**?**] used to replace the update functions with LSTM DNNs that learn how to optimize the variables u_i, w_i, and v_i for a given channel H.

C. Recurrent Neural Network for WMMSE

The authors in [?] built their architecture following the work of [?] who applied recent advancements in deploying DNNs in unfolded optimization problems. Specifically, [?] described the steps as in Table 3.

1) Map iterations of optimization algorithm to DNN
2) Fix number of iterations to compute availability
3) Optimize hyper-parameters within iteration allowance

Following the above algorithm, the authors in [?] used Tensorflow to create three LSTM networks, one for learning to update each variable u_i, w_i, and v_i based on the global loss function. This preserved the original structure of the unfolded WMMSE problem and creates the following algorithm as published by [?]:

```
1  Given: global loss function F(u, w, V), H.
2  Initialized: V_0, u_0, and w_0.
3  for t ← 1, 2, ..., T do
4      i, j, k, s = 1
5      while i ≤ I do
6          Δu = m_u(∇f(u^(i-1)), C_u^(i-1), θ_u^s)
7          u^(i) ← u^(i-1) + Δu  i = i + 1
8      end
9      u_t = u^(I)
10     generate f(w) with u_t, V_{t-1}
11     while j ≤ J do
12         Δw = m_w(∇f(w^(j-1)), C_w^(j-1), θ_w^s)
13         w^(j) ← w^(j-1) + Δw  j = j + 1
14     end
15     w_t = w^(J)
16     generate f(V) with w_t, u_t
17     while k ≤ K do
18         ΔV = m_V(∇f(V^(k-1)), C_V^(k-1), θ_V^s)
19         Ṽ^(k) ← V^(k-1) + ΔV
20         V^(k) = Ω_D{Ṽ^(k)}
21         k = k + 1
22     end
23     V_t = V^(K)
24     generate f(u) with V_t, w_t
25     F(V_t, u_t, w_t) ← u_t, w_t, V_t
26     while s ≤ t/t_up do
27         L_F^s = (1/t_up) Σ_{t_s=(s-1)t_up+1}^{s t_up} ω_{t_s} F(V_{t_s}, w_{t_s}, u_{t_s})
28         θ_V^{s+1} = θ_V^s - α_V ∇_{θ_V^s} L_F^s
29         θ_u^{s+1} = θ_u^s - α_u ∇_{θ_u^s} L_F^s
30         θ_w^{s+1} = θ_w^s - α_w ∇_{θ_w^s} L_F^s
31         s = s + 1
32     end
33 end
```

Fig. 1. Algorithm from [?] for implementing the unfolded WMMSE algorithm using DNNs.

The algorithm in figure 1 shows the complete algorithm implemented by [?] that was sought to be replicated and improved in this paper.

II. EXPERIMENTATION AND MODEL

III. RESULTS

A. Automatic Differentiation

B. Exploding Gradients

IV. CONCLUSION

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