Machine Learning for Reliable MIMO Systems

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***Abstract*—The recent rapid increase in users of cellular networks necessitates the use of new technologies to meet this demand. Massive multiple input multiple output (MIMO) communication systems have the potential of significantly increasing the user capacity of the coming 5G cellular networks. Massive MIMO systems have especially shown great advantages for millimeter wave (mmWave) systems. However, dynamic performance optimization of massive MIMO systems requires large and complex models, and physically testing any designed algorithms for such a system is not feasible due to the scale and complexity of such networks. To address this, the current IRES project seeks to apply machine learning to both mmWave and traditional massive MIMO systems. This project will also implement a MIMO software defined radio system to test machine learning algorithms and make projections from simulations on larger systems.**

***Index Terms*—Massive MIMO, Millimeter Wave, Machine Learning, Neural Network, Software Radio.**

I. Introduction

MASSIVE multiple input multiple output (MIMO) wireless systems are critical to present and future wireless communication systems for both traditional [1], [2] and millimeter wave (mmWave) technologies [3]. Future wireless cellular networks will see a combination of these technologies and more to achieve the desired network performance [1].

Machine learning shows great promise when applied to the complex optimization situations that are a part of massive MIMO [4]–[6]. Common algorithms used to model these systems like stochastic geometry, combinatorial optimization, and game theory require significantly more complex analysis and computing resources than traditional machine learning algorithms. This makes machine learning algorithms ideal for tasks such as beamforming, load balancing, channel estimation, and spectrum optimization because of the high complexity models and dynamic nature [5]–[7]. A hardware platform consisting of the LimeSDR development kit and the Lime Suite signal processing environment will be used to analyze machine learning algorithms for MIMO wireless networks. The memory usage and execution speed will be analyzed and projected onto massive MIMO Simulations.

The reliability and throughput of mmWave systems is greatly decreased by the presence of blockages between the base station and the user [3]. This IRES project seeks to extend the work done in [3] by examining a different system model. The new system model has stationary transmitters and receivers and a moving obstruction. A gated recurrent unit (GRU) is used to track past beamforms and then predict the probability that the next beamform will be blocked. The first step is to model the described situation using the DeepMIMO dataset as described in [8]. The data will then be used to train and test the recurrent neural network to obtain the desired results.

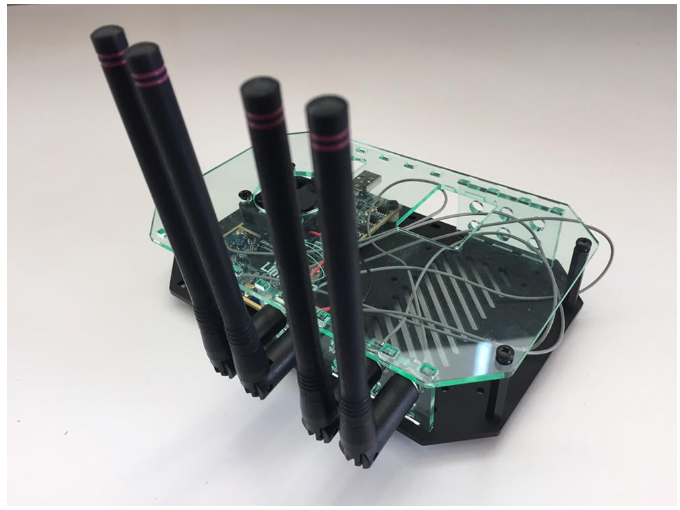

Fig. 1. The LimeSDR development kit. This is a Feild Programmable RF 2x2 MIMO transmitter and reciever with a continuous frequency range of 100MHz to 3.8GHz [9].

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