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Massive MIMO Signal Decoding: A Deep Learning Approach

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ABSTRACT: Massive-multiple-input-multiple-output (M-MIMO) is one of the key techniques for the future 5G wireless communication systems. For successful communication a M-MIMO decoder is required which is less complex, faster while decoding and provides better symbol-error-rate (SER). The current sphere decoder (SD) scheme for M-MIMO scenario is close to ideal system, performs well, but the computational cost is directly correlated with the quantity of nodes visited during the tree search and the signal-to-noise ratio (SNR). In this study, we discuss signal detection in multiple-input, multiple-output (MIMO) systems with Rayleigh fading channel. An idea for a Deep Learning Detector (DLD) is put forth using neural network methods. Following an offline training phase, the DLD approach may identify signals sent in an impulsive noise channel. While performing well, the DLD detection procedure is less difficult than the typical SD complexity. Even more intriguing is the fact that, unlike SD detectors, which have an exponential complexity over the SNR, DLD has a constant computational complexity throughout SNR.

KEYWORDS: Massive-MIMO, Deep Learning, Rayleigh Fading, MIMO Decoder, Computational Complexity.

I. INTRODUCTION

Multi antenna technique such as Multiple input Multiple output (MIMO) technology is one of the key techniques for future 5G developments. This enables the use of large antenna array to increase the data rates, coverage, link reliability and enhance the spectral efficiency by using the multipath characteristics of the wireless channel. Conventionally, the user equipment communicates with the base station (BS) in orthogonal time-frequency resource which is not optimal from resource point of view. In wireless communications, the variability of the transmission channel may significantly degrade data transmission. For example the presence of high voltage near electrical power stations creates fluctuations in the channel known as impulsive noise that reduces the overall transmission rate between a source and a destination [1]. In this paper we explore receiver design for channels impaired by such impulsive noise. One of the major challenges in MIMO communication sys- tems is to improve the bit error rate (BER) without increasing the complexity of the detector at the receiver [2]. Fig. 1 represents the massive-MIMO scheme.

In next generation communication system a diverse range of impairments such as amplifier distortion, quantization loss, propagation loss, fading, multipath need to be addressed. Not only this, the degree of freedom required to successfully operate the 5th Generation communication system goes on increasing day by day. These impairments along with increasing number of degree of freedom makes current system very difficult to optimise if not impossible. Currently available MIMO detectors has solid roots in mathematics and statistics and these detectors only captures the approximate behaviour of the system. That's why it is not possible to perform end-to-end optimization of the communication system in practical and these systems give suboptimal performance.

In 5G communication technologies for higher data rate and reliability requirement it is necessary to implement a large number of antenna array on transmitter as well as receiver side. Large number of antenna makes this system very complex during detection and the receiver system need to process very large matrix operations. These increasing complexity requirement makes conventional system prone to bit error and higher time consuming while decoding the message.

In the past few years Deep Learning shows a great potential in the field of image processing, computer vision and natural language processing. Deep learning algorithms captures the practical state of the system and learns the task beyond human level of accuracy [6],[7 An introduction to deep Learning]. In deep learning a neural network algorithm learns to perform classification task directly from the data fed to it. In neural network, there are two phases, training phase and classification phase. During training phase the deep network takes known data and adjust its weight of

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network connection in order to meet the correct result. During classification phase, the deep network uses its intelligence to provide the correct output.

The optimal receiver can be found by using the maximum a posteriori probability (MAP) algorithm. However, its complexity increases exponentially with respect to the modulation order, the number of transmit antennas and the SNR. Hence, a sub-optimal low complexity detector is needed. In the high accuracy type of detectors the sphere decoder (SD), based on a tree search algorithm, and was proposed. The SD offers a better computational complexity than MAP [3].

In this study, deep neural networks are used to tackle the issue of symbol identification on MIMO channels with impulsive noise. The following list summarises this paper's significant contributions:

- ✓ In the presence of impulsive noise channels, we suggest a new deep learning decoder (DLD) for MIMO communications.
- ✓ The suggested deep neural network may be trained on an impulsive noise channel and still perform well on a Gaussian channel, as demonstrated by our demonstrations.
- ✓ The proposed approach also achieves lower computational complexity with comparable detection performance to the spherical decoder, according to our numerical results.

Following is how this document is structured for the remaining portions. The related work is briefly described in Section II, and the system model and problem statement are presented in Section III. Section IV represents the research methodology. Section V discusses about the simulation and results. Finally section VI concludes the work.

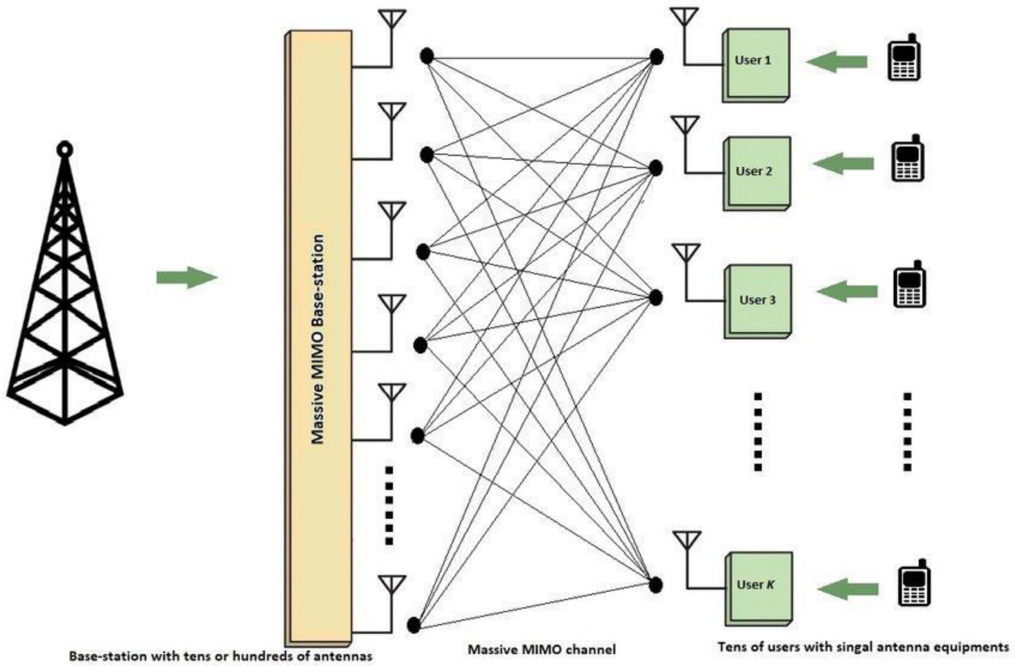

Fig. 1: Massive MIMO scenario

II. BACKGROUND WORK

Now a day's people uses deep learning models to solve the problem of communication system. Apart from this, Deep Learning based MIMO Detector does not requires a statistical and mathematical model to implement the communication system. Deep learning models can be optimized for a particular hardware configuration and a particular wireless channel model. This end to end optimization of the system is done through rigorous training of the Deep Network on the data obtained from communication hardware and channel models in real world. This Deep detector captures the hardware and channel system model in a better manner than its conventional MIMO detectors such as Maximum likelihood (ML) detector, Minimum mean square error (MMSE) detector or zero forcing (ZF) receiver [7 Sparsely Connected Neural Network]. Several researchers have already investigated deep learning based MIMO Detectors. Resent development in Deep Learning for communication develop alternative solutions to enhance

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conventional communication system. In [An introduction to deep learning (self)] a deep auto encoder based communication system has been proposed in which whole transmitter-channel-receiver system is assumed as a single end-to-end deep learning system and optimised accordingly. In [Deep learning based channel estimation] the MIMO channel estimation is formulated as image recovery problem. In this Deep learning based LDAMP network is used to recover the enhance MIMO channel at the receiver. In [Deep learning for massive mimo csi feedback Deep learning based CSI feedback] the MIMO channel is estimated and compressed using DEEP network at receiver and receiver feed this compressed CSI back to transmitter where Deep network based decoder is used to decode the MIMO channel. In [12] and [13] a multi-layer neural network Detection network has been proposed in which author uses a real valued Gaussian random channel to train the network. For creating the deep network authors first increase the input data to a higher dimension and also add some standard non linarites into it. These additional non linearity increases the complexity of the network and this network takes longer time for training as well as decoding.

Deep learning is becoming more popular in applications like MIMO. A thorough analysis of the various MIMO communications-related topics, such as channel estimation, detection, end-to-end system design, resource management, power control, etc., is offered in [8]–[11]. The authors of [12] suggested an auto-encoder. They described an Extreme Learning Machine approach to categorise the input signals of an OFDM MIMO system after using an auto-encoder as a feature extractor while taking into account the signal properties. Their suggested approach has a similar level of complexity to baseline techniques while achieving high detection accuracy.

Similar proposals were made by the authors of [13] and [14] for the creation of an end-to-end communication system and the use of auto-encoders to teach transmitter/receiver implementations and signal encoding/decoding procedures together. The performance of the simulation findings over an additive white Gaussian noise channel is comparable to that of earlier investigations. However, their solution's scalability continues to be problematic. Auto-encoder practical applications are also discussed in [15], [16].

In [17], another intriguing solution was put out. There, a deep learning structure for molecular/optical network symbol detection was analysed. One significant assertion in [17] is that neural network detectors function effectively even when the channel model is unknown. Their simulation findings show that the Viterbi detector performs better than a Poisson channel model. According to [18], deep learning could be used to jointly estimate channel state information (CSI) and detect/recover transmitted symbols using the calculated CSI. Their simulation results demonstrate that, despite being less sophisticated, their method can detect transmitted symbols with comparable accuracy to the lowest mean-square error estimator.

III. SYSTEM MODEL

Consider uplink of a Multi User MIMO system where NT single transmit antenna users used to transmit data to a base station (BS) having NR receive antennas. The propagation path between each receive-transmit antenna pair is assumed to be Frequency flat fading and remain constant for one transmitted packet. The standard MIMO channel model for this scenario is given below:

$$\mathbf{y} = \mathbf{Hx} + \mathbf{n} \qquad 1$$

Where is received message vector, is unknown transmitted message vector of equiprobable and independent symbols, is MIMO channel matrix and is independent identically distributed Gaussian noise of zero mean and variance . In this paper we have assumed that channel matrix H has random coefficients with known distribution and is perfectly known to the receiver.

The main goal of a MIMO detector is to detect the transmitted signal of all the users or antennas from the received signal with minimum error. There are so many classical MIMO detectors available in theory which are being used in practical MIMO receivers. One of the classical MIMO detector known as Maximum Likelihood (ML) detector gives near optimal performance. It minimizes the joint probability of error of all the symbols simultaneously. ML decoder estimates the transmitted signal based on the nearest Euclidian distance from the knowledge of received signal and the channel states. Minimizing the joint probability of error means maximizing the probability of correctly estimating .i e

$$P\left(\mathbf{s} = \hat{\mathbf{s}} \middle| \mathbf{y}, \mathbf{H}\right) = \frac{P\left(\mathbf{s} = \hat{\mathbf{s}}\right) f_{y|s,H}\left(\mathbf{y} \middle| \mathbf{s} = \hat{\mathbf{s}}, \mathbf{H}\right)}{f_{y|H}\left(\mathbf{y} \middle| \mathbf{H}\right)} \qquad 2$$

After maximizing expression (2), one can get the solution which is known as ML estimator:

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$$\hat{\mathbf{x}}_{ML} = \underset{\hat{\mathbf{x}} \in \{\pm 1\}^{N_T}}{\arg\min} \|\mathbf{y} - \mathbf{H}\hat{\mathbf{x}}\|^2 \quad 3$$

Since ML decoder searches all the possible signals, with increasing number of users and receive antennas, the computational complexity increases exponentially and requires a search of $O\left(2^{N_T}\right)$. Figure 2 represents the massive-MIMO system model.

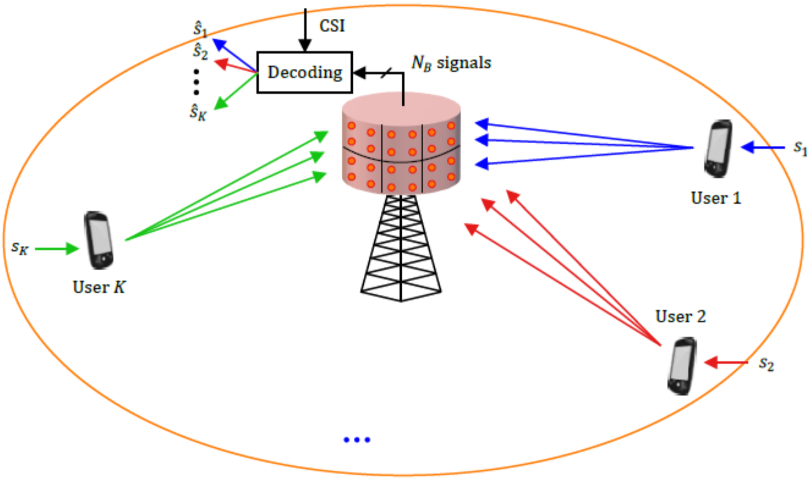

Fig. 2: Massive-MIMO system model

IV. RESEARCH METHODOLOGY

In this work, the architecture of the MIMO detector is based on the projected gradient descent where:

$$\hat{\mathbf{x}}_{l+1} = \prod\left[\hat{\mathbf{X}}_l - \lambda_l \frac{\partial \|\mathbf{y} - \mathbf{H}\mathbf{x}\|^2}{\partial x}\bigg|_{\mathbf{x}=\hat{\mathbf{x}}_l}\right] \quad 4$$

Where $\prod$ represents a nonlinear projection operator, the estimate of x and the step size in lth iteration is and respectively. Our deep learning based MIMO decoder follows the same paradigm. It consists of L repetitive layer where each layer consists of some sub layers. The architecture of the proposed MIMO detector is shown in Fig.1. This detector takes channel matrix H, received signal y and xl as input where H and y is fixed for all the layers and xl is the estimate of x in the l-1th layer of this detector. One main layer of this network has two sub layers, which are represented through following mathematical expression.Here, ReLu is the rectified linear unit defined as ReLu(x) = max{0, x}, l = 1,2,3,…L, and is a piecewise linear signum operator defined in [Deep MIMO Detection] equation (4) for different value of t.The expression of and is derived from gradient descent algorithm where we are applying standard non linearity in the terms of Wkl as random weight and bkl as bias term in lth layer. These non-linearity lifts the input to a higher dimension which are common in Deep learning. The dimension of p, q and r is whereas after addition of p,q and r, the dimention of is also 1x1.

V. SIMULATION RESULTS

In this section we have trained the proposed deep learning based MIMO decoder described in previous section and evaluate the Bit Error Rate (BER) performance, complexity and timing analysis over a wide range of SNRs.

For training of this model, we have generated the channel matrix H having channel coefficients as independent identically distributed Gaussian random variable with mean zero and variance one (N (0,1)). For each batch the matrix H is independently generated in each iteration. We have compared the performance of the proposed decoder with following MIMO decoding algorithms.

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ZF: This is the least square Zero Forcing (ZF) detector also known as decorrelator [1 Deep MIMO Detector].MMSE: This is Minimum mean square error based MIMO detector. This detector provides optimal solution.SDR: Semi Definite Relaxation (an optimization technique) based MIMO decoder.SD: Sphere decoding algorithm based MIMO decoder.We have simulated all these conventional MIMO system in Matlab and Tensorflow backend with numpy in Python is used to simulate the proposed Deep Learning based MIMO decoder using GPU backend.

A. Accuracy Performance

We have simulated the proposed MIMO decoder for different number of Transmit (Tx) and Receive (Rx) antennas in a wide range of SNRs. In first experiment we have chosen 30 Tx antenna with 60 Rx antenna and results are presented in Fig. 4. In this experiment, we obtained that our DNN based MIMO detector shows better performance than ZF and DetNet. Compared to SDR, our DNN based MIMO decoder gives better performance up to 13 dB SNR value and after 13 dB both the decoders have same accuracy performance. In second experiment, we have chosen 20 Tx antenna with 30 Rx antenna and results are presented in Fig. 5. In this experiment, we obtained that our presented MIMO detector shows better performance than ZF and DetNet whereas it manages to provide similar accuracy than SDR in low SNR range.

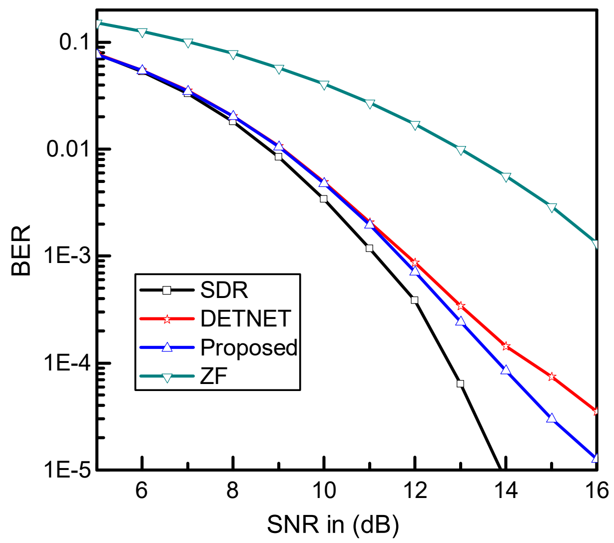

Fig. 3: Accuracy performance (BER vs SNR) graph of MIMO decoders. For Tx= 20, Rx= 30 antennas.

B. Network Convergence Analysis

One of the main aspect of any decoding algorithm in communication system is timing and complexity analysis means how much time a decoder takes to decode one frame of message. For timing analysis we have simulated DetNet, ZF and proposed decoder on the same hardware platform.

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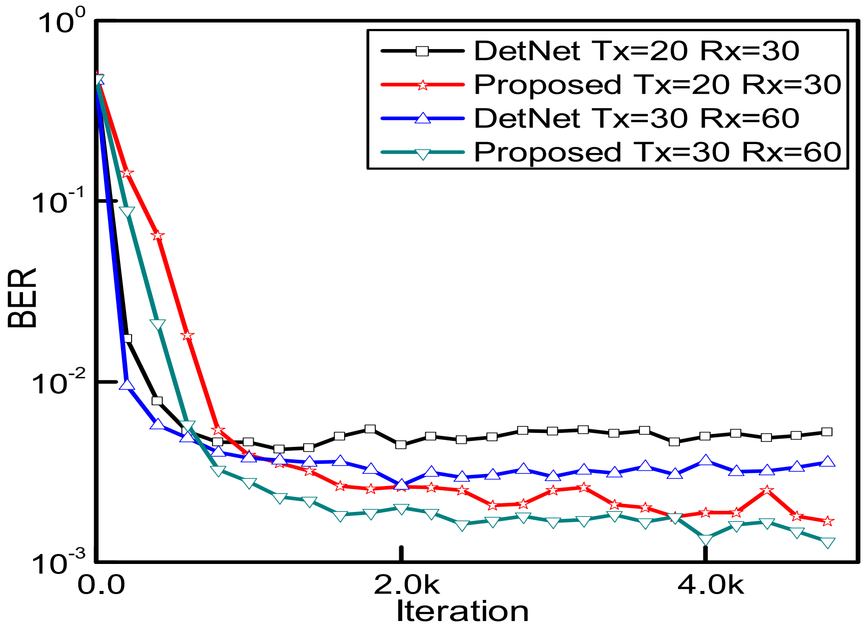

Fig. 4: Network convergence speed.

In Fig. 6, we have shown the graph of time taken by DetNet and SDR based decoders for a wide range of SNR. In this graph on y axis, values are normalized with respect to time taken by our presented decoder. This simulation shows our proposed decoder runs 164 times faster than DetNet whereas it runs 28200 times faster than SDR based MIMO decoder. In Table I. complexity of the deep learning networks DetNet and the proposed detector is presented.

VI. CONCLUSION

In this paper we have presented deep neural network based MIMO detector and simulated its accuracy as well as timing and complexity performance for time-varying randomly generated flat fading Gaussian channels. The architecture and simulation results of presented MIMO decoder is providing an exciting and new approach to MIMO system design that optimizes the wireless communication system using architecture of deep neural networks. This is a significant increment from conventional MIMO decoders available currently and has many issues which still need to be understood and made to operate efficiently with real world constraints.

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