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An Efficient Deep Learning Network for MIMO Detection using Bayesian Optimization

***Abstract**. Despite the many advantages of Multiple Input Multiple Output (MIMO) Wireless Communication systems, their receiver design is quite a challenging task as there is always a trade-off between the receiver performance and the computational complexity. If performance is optimum, the computational complexity is exceptionally high and vice-versa. In this paper by using Bayesian Optimization, the performance of an AI-based MIMO receiver algorithm, called DetNet is improved. The results show an improvement in detection performance without any increase in time complexity.*

***Streszczenie.** Pomimo wielu zalet systemów komunikacji bezprzewodowej MIMO (Multiple Input Multiple Output), ich konstrukcja odbiornika jest dość trudnym zadaniem, ponieważ zawsze istnieje kompromis między wydajnością odbiornika a złożonością obliczeniową. Jeśli wydajność jest optymalna, złożoność obliczeniowa jest wyjątkowo wysoka i odwrotnie. W tym artykule, dzięki zastosowaniu optymalizacji bayesowskiej, wydajność algorytmu odbiornika MIMO opartego na sztucznej inteligencji, zwanego DetNet, została poprawiona. Wyniki pokazują poprawę wydajności wykrywania bez żadnego wzrostu złożoności czasowej. (**Wydajna sieć głębokiego uczenia do wykrywania MIMO przy użyciu optymalizacji bayesowskiej**)*

Keywords: MIMO, Bayesian Optimization, Deep Learning, Bayesian Optimization, MIMO Detection, Hyperparameter Tuning.
Słowa kluczowe: MIMO, optymalizacja bayesowska, głębokie uczenie, optymalizacja bayesowska, wykrywanie MIMO.

Introduction

It is projected that the communication sector will continue to expand quite quickly because it is essential to the innovation and profusion of different economic sectors, including transportation, consumer electronics, healthcare, agriculture, finance, and services [1]. The future wireless networks necessitate a variety of uses such as Highly Digitized Smart Cities, Vehicle-to-everything (V2X), XR applications, Brain Computer interfaces, Flying vehicles, robotization, etc [2], [3]. Thus, wireless communication systems need to upscale for meeting the needs of future technologies.

Multiple Input Multiple Output, abbreviated as MIMO systems, include multiple antennas on both the transmitter and receiver sides and form the essential component of various wireless systems as these offer various advantages such as an increase in reliability due to Diversity Combining, a decrease in Bit Error Rate (BER), manifold increment in data rate due to Spatial Multiplexing, better Quality-of-service(QoS), improvement in Energy Efficiency, etc [4]. However, the main barrier that affects the performance of MIMO systems is the not-so-good performance of detection techniques due to the trade-off between high Computational Complexity and poor Error rate performance. Reproducing a message chosen at one point either precisely or roughly at another location is the fundamental issue of communicating [5].

In MIMO systems, at the signal receiver (detection) side, multiple signals arriving simultaneously at multiple receive antennas from multiple transmit antennas, need to be detected jointly. For example, consider a 4x2 MIMO system that has 4 antennas at the transmitting end and 2 antennas at the receiving end. Here, four antennas are sending four distinct signals simultaneously which are received by both the antennas at the receiver. These signals must be detected jointly.

There are different types of MIMO receivers in literature [6]. Optimal MIMO receivers such as Maximum Likelihood (ML) and Maximum-a-priori (MAP) receivers, though optimal, are impractical as their complexity increases exponentially. Though Linear MIMO detectors are preferred, their performance is limited. Spherical Decoder (SD) is used but these provide high efficiency only for high SNRs. Lattice reduction (LR) techniques with SD may be used to improve performance. Also, for spatially multiplexed MIMO schemes, using transmission schemes such as V-BLAST (Vertical/horizontal layered space-time transmission) and D-BLAST (Diagonal Bell labs layered space-time transmission), advanced MIMO receivers may be used such as Successive Interference Cancellation (SIC), Ordered SIC (OSIC), LR, etc. Several metaheuristic-based MIMO detectors have also been developed as mentioned in [7].

Using Deep Learning (DL) techniques in MIMO detectors, there is no need to compromise between the complexity of the system and BER. Optimal MIMO detectors (e.g., Maximum Likelihood Detector (MLD)), have good BER performance but have impractical computational complexity. However, MIMO detectors such as MLD can be easily represented by DL methods, i.e., Deep Neural Networks, and with very low complexity, as these work as general function approximators [8].

The rest of the paper is organized as follows. The next section presents the need for model-driven Deep Learning models and one such model employed for MIMO detection, known as DetNet is described. After that, Bayesian Optimization algorithm and its application for tuning of hyperparameters is described. The next section highlights the new work done for enhancing the performance of DetNet. The proposed algorithm is called BODetNet. After that, the simulation results show the supremacy of BODetNet over DetNet in terms of BER. Also, the model is an Interpretable AI model and that is shown using Partial Dependence Plots. This is followed by Conclusions and References.

AI-based MIMO receiver: DetNet

Though data-driven Deep Learning (DL) methods have been widely applied to physical layer communication, the training of such networks needs extensive computing resources, a large amount of time, and a huge dataset, both of which are not easily found in communication networks. These treat the communication system like some sort of "black box," for which, the training requires large quantities of data.

Model-driven Deep Learning (DL) methods come to the rescue by reducing the requirement of many resources for computation and extensive time for training as these networks are constructed by exploiting already known domain knowledge [9].

DetNet (Detection Network) [10] is a model-driven DL based MIMO detection algorithm. It was created using a Projected Gradient Descent Method (or pgdm) for neural network ML detection [11]. It outperforms the traditionally used expectation propagation-based MIMO detectors and iterative MIMO detectors such as AMP which fail to provide optimal performance under difficult conditions, where the channel distribution is unknown. With respect to Symbol Error Rate (SER), DetNet also outperforms MIMO detectors based on sphere decoding. It achieves greater accuracy than Semi Definite Relaxation (SDR) MIMO detectors and is greater than 30 times faster than it. DetNet takes input in the form of received signals and perfect Channel State Information (CSI). It has proven to be robust in both cases of difficult fixed channel conditions and of varying channel case, having a known channel distribution. Real-time, Near-optimal performance is possible by using DetNet as it is quite fast. It is able to work on different models by training only once. The fully connected architecture, abbreviated as 'FullyCon', as shown in Fig. 1 is the basic Deep Neural Network architecture. which is made up of 'L' layers in which each layer's output is fed to the next layer's input. It only has a few parameters that need to be optimised. and doesn't exploit channel H.

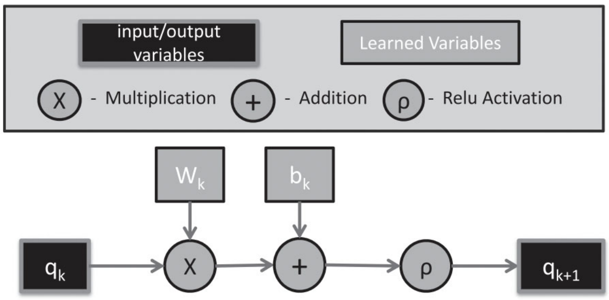

Fig. 1. Representation of Single layer of FullyCon architecture [12].

As compared to Fullycon, DetNet, as shown in Fig. 2, utilizes channel information and has more parameters to optimize. DetNet's weighted average of one layer is fed to the next.

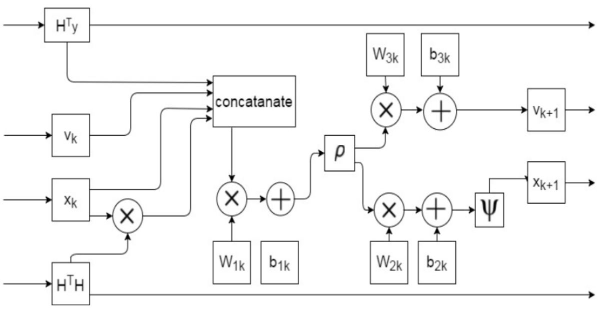

Fig. 2. Representation of Single layer of DetNet. [12].

Bayesian Optimization (BO) for Hyperparameter Tuning (HT)

Bayesian optimization (BO) is a sequential design approach that does not make any functional form assumptions and is used for the global optimization of black-box functions. Usually, it is used to improve difficult-to-evaluate functions that are not computationally inexpensive. In various ML algorithms, the tuning of learning parameters and modeling of hyperparameters must be done quite carefully and frequently. However, it is not an easy task and it needs expert experience and sometimes brute force searching. Thus, automatic approaches are required [13]. The most popular ways of hyperparameter tuning for ML are Manual Tuning, Grid Search and Random Search, out of which, Bayesian optimization (BO) is the best.

Proposed system

In this work, BO is employed for Hyperparameter Tuning of the DetNet MIMO detector. Expected Improvement (EI) is employed as an acquisition function, while Gaussian Process (GP) is used as a surrogate function. The optimized MIMO detection network is termed as BODetNet, as depicted in Fig. 3.

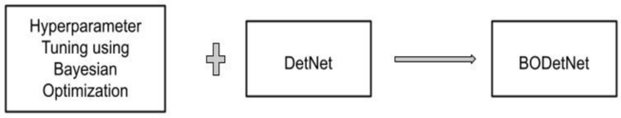

Fig. 3: Simplified model of the proposed

To the best of our knowledge, by doing an extensive literature survey, we have found out that BO has not been applied on DetNet for its Hyper Parameter Tuning.

Simulation parameters & Results

The hyperparameters obtained after applying Bayesian Optimization and the results obtained after using these hyperparameters on the MIMO receiver model are listed in this section.

Optimized Hyperparameters

As discussed in earlier sections, hyperparameters denote the configurations that have to be set before the training of a model in order to customize it to the dataset. The best set of hyperparameters have been found out using Bayesian Optimization and are listed in Table 1.

Table 1. The parameters of the sensor

Hyperparameter name	Hyperparameter value	Description of the Hyperparameter
res_alpha	0.7348030690540688	The proportion of the previuos layer output to be added to the current layers output.
decay_factor	0.689345364283937	It is the factor which decay_step_size steps the learning rate decay.
decay_step_size	1161	Each decay_step_size steps the learning rate decay by decay_factor.
train_batch_size	4643	Batch size during training phase.
startingLearningRate	0.7348030690540688	The initial step size of the gradient descent algorithm.

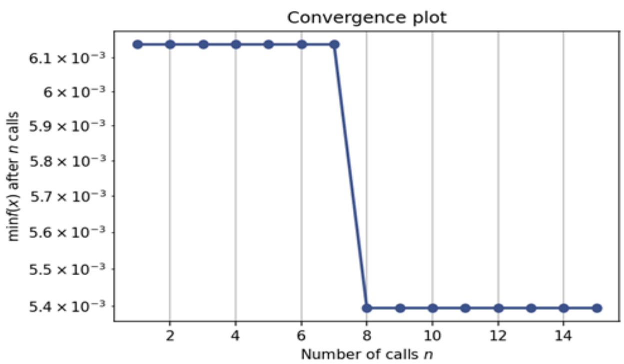

Fig. 3. Convergence plot

The convergence plot in Fig. 3 depicts that after 8 iterations, the results have converged and there is no further improvement in the value of BER. The results show 24% improvement in BER as compared to DetNet [12] especially, at low SNR values,as shown in Fig. 4 and Table 2.

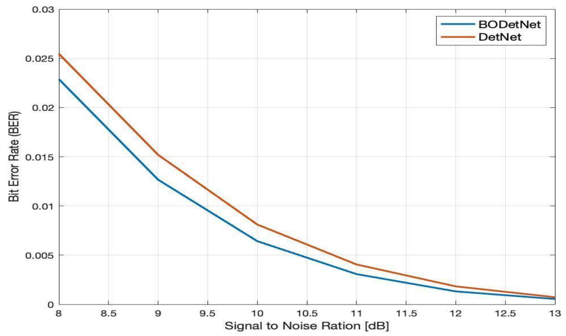

Fig. 4. BER versus SNR graph

Table 2. Comparison of DetNet and BoDetNet results

SNR	BER for DetNet	BER for BODetNet
8	0.0254615	0.0228825
9	0.0151945	0.012667
10	0.0081115	0.00642
11	0.0040525	0.0030725
12	0.001827	0.001316

Interpretable Machine Learning (IML) using Partial dependence plot with categorical value

Interpretability in ML and DL models is of utmost importance in future wireless networks. It is necessary to have insight regarding how these models work for the datasets and if there is any problem, it can be identified and resolved. Thus, using Explainable and Interpretable ML and DL, the models are no longer 'Black Boxes'. IML has been suggested to be applied to gain insights from the data obtained during HPO with Bayesian optimization (BO) [14].

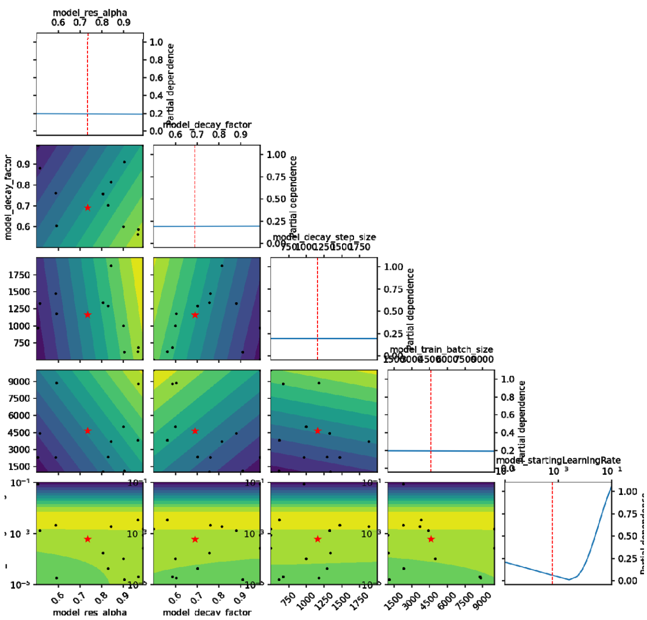

Fig. 5. PDP with categorical value

One of the methods is by using Partial Dependence Plots (PDPs). PDPs depict how the predictions of the model are affected by each variable or predictor [15]). The PDPs describe how predicted outcome of the ML or DL model is marginally effected from one or two features. It can also give information about the relationship between target and feature i.e, whether it is monotonic, linear or more complex [16]. PDPs plotting two input features depict the interplay of both. These plots also describe how various inputs are affecting the target response by taking marginal effect of remaining input features. (Partial Dependence and Individual Conditional Expectation plots). From Fig. 5, the effect of anyone hyperparameter on others can be interpreted. It can also be interpreted that the startingLearningRate hyperparameter has themost effecton the target results.

Conclusions

The proposed BODetNet MIMO detection algorithm shows successful improvement of the DetNet structure that has been showcased in terms of decrease in BER via simulation. In this paper, we have proposed an improvement of DetNet which is an AI-based MIMO detection algorithm.

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