



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJIRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 11, Issue 2, February 2022

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 7.569



9940 572 462



6381 907 438



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Survey on Learning-Based Signal Detection for 5G MIMO-OFDM System

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ABSTRACT: In recent time, the demand for multimedia data services has grown up rapidly. One of the most promising multi-carrier system, Orthogonal Frequency Division Multiplexing (OFDM) forms basis for all 4G wireless communication systems due to its large capacity to allow the number of subcarriers, high data rate and ubiquitous coverage with high mobility. OFDM is significantly affected by peak-to-average-power ratio (PAPR). Unfortunately, the high PAPR inherent to OFDM signal envelopes will occasionally drive high power amplifiers (HPAs) to operate in the nonlinear region of their characteristic curve. This paper emphasis mainly on the PAPR reduction of OFDM system using partial transmits sequence (PTS) and precoding techniques. Some other techniques such as amplitude clipping have low-complexity; on the other hand, they suffer from various problems such as in-band distortion and out-of-band expansion. Signal companding methods have low-complexity, good distortion and spectral properties; however, they have limited PAPR reduction capabilities. Advanced techniques such as coding, partial transmit sequences (PTS) and selected mapping (SLM), have also been considered for PAPR reduction.

KEYWORDS: PTS, STBC, MIMO, OFDM, PAPR

I. INTRODUCTION

A combination of multiple input multiple output (MIMO) and orthogonal frequency division multiplexing (OFDM) (MIMO-OFDM) is an emerging technology for high speed data multi-carriers transmission in future wireless communication network systems such as digital audio broadcasting (DAB), digital video broadcasting (DVB), medical body area networks (MBANs) applications, the fourth and the fifth generation (4G,5G) of mobile network. In MIMO-OFDM framework, the yield is the superposition of numerous sub-bearers. At whatever point, the stages and frequencies of these bearers coordinate soundly, prompt power yields may increment significantly and end up higher than the mean energy of the powerful intensifier (HPA) bringing about extensive PAPR [1]. Lot of research work has been done for solving the problem of PAPR that concerns all kind of multicarrier signals. So, many techniques have been proposed such as clipping [2], tone reservation [3], nonlinear transformations [4], coding [5], selecting mapping (SLM) [6] and partial transmit sequence (PTS). Modified approaches of PTS are proposed in that produce better results; however, the computational complexity is still remaining unsolved totally. In this paper an approach is proposed to reduce the PAPR in STBC MIMO-OFDM systems with less computational complexity. So, the mean idea is based on separating the input vector data into real and imaginary parts for computational simplification reasons and then C-A-PTS is applied individually on these parts, moreover, PAPR is conjointly optimized in real part and imaginary part for the first antenna and by symmetry property the optimum weighting coefficient is deduced for the second antenna without any extra optimization which leads to decreasing of the complexity of the computation [7]. This approach is applied in STBC MIMO-OFDM systems.

II. LITERATURE REVIEW

Ke He et al. [1], this paper aims to answer the question: How to devise a robust and effective maximum likelihood estimator to accurately estimate the signal with unknown noise statistics in multiple-input multiple-output (MIMO) systems? In practice, there is little or even no statistical knowledge on the system noise, which in many cases is non-Gaussian, impulsive and not analyzable. Existing detection methods have mainly focused on specific noise models, which are not robust enough and cannot perform well in the presence of noise with unknown statistics. To tackle this issue, we propose a novel detection framework in order to perform an effective maximum likelihood estimate (MLE)

and thus, to recover the desired signal. Our framework is a fully probabilistic one, and can efficiently approximate the unknown noise distribution through a normalizing flow. Importantly, this framework is driven by an unsupervised learning approach without labels, where only the noise samples are required. To reduce the computational complexity of the MLE, we further present a low-complexity version of the detector, by utilizing an initial estimation, using the Gaussian generalized approximate message passing (G-GAMP) algorithm. Simulation results show that our framework outperforms other existing algorithms in terms of bit error rate (BER), while it can reach the performance bound of MLE in Gaussian noise. Moreover, the low-complexity version can outperform the Euclidean distance based MLE (E-MLE) in highly impulsive noise environments.

C. Li et al. [2], have study a multiuser mobile edge computing (MEC) network, where tasks from users can be partially offloaded to multiple computational access points (CAPs). We consider practical cases where task characteristics and computational capability at the CAPs may be time-varying, thus, creating a dynamic offloading problem. To deal with this problem, we first formulate it as a Markov decision process (MDP), and then introduce the state and action spaces. We further design a novel offloading strategy based on the deep Q network (DQN), where the users can dynamically fine-tune the offloading proportion in order to ensure the system performance measured by the latency and energy consumption. Simulation results are finally presented to verify the advantages of the proposed DQN-based offloading strategy over conventional ones.

J. Cui et al. [3], Unmanned aerial vehicles (UAVs) are capable of serving as aerial base stations (BSs) for providing both cost-effective and on-demand wireless communications. This article investigates dynamic resource allocation of multiple UAVs enabled communication networks with the goal of maximizing long-term rewards. More particularly, each UAV communicates with a ground user by automatically selecting its communicating user, power level and subchannel without any information exchange among UAVs. To model the dynamics and uncertainty in environments, we formulate the long-term resource allocation problem as a stochastic game for maximizing the expected rewards, where each UAV becomes a learning agent and each resource allocation solution corresponds to an action taken by the UAVs. Afterwards, we develop a multi-agent reinforcement learning (MARL) framework that each agent discovers its best strategy according to its local observations using learning. More specifically, we propose an agent-independent method, for which all agents conduct a decision algorithm independently but share a common structure based on Q-learning. Finally, simulation results reveal that: 1) appropriate parameters for exploitation and exploration are capable of enhancing the performance of the proposed MARL based resource allocation algorithm; 2) the proposed MARL algorithm provides acceptable performance compared to the case with complete information exchanges among UAVs. By doing so, it strikes a good tradeoff between performance gains and information exchange overheads.

Y. Xu et al. [4], marriage of wireless big data and machine learning techniques revolutionizes wireless systems by introducing data-driven philosophy. However, the ever exploding data volume and model complexity will limit centralized solutions to learn and respond within a reasonable time. Therefore, scalability becomes a critical issue to be solved. In this article, we aim to provide a systematic discussion of the building blocks of scalable data-driven wireless networks. On one hand, we discuss the forward-looking architecture and computing framework of scalable data-driven systems from a global perspective. On the other hand, we discuss relevant learning algorithms and model training strategies performed at each individual node from a local perspective. We also highlight several promising research directions in the context of scalable data-driven wireless communications to inspire future research.

H. He et al. [5], have investigate the model-driven deep learning (DL) for MIMO detection. In particular, the MIMO detector is specially designed by unfolding an iterative algorithm and adding some trainable parameters. Since the number of trainable parameters is much fewer than the data-driven DL based signal detector, the model-driven DL based MIMO detector can be rapidly trained with a much smaller data set. The proposed MIMO detector can be extended to soft-input soft-output detection easily. Furthermore, we investigate joint MIMO channel estimation and signal detection (JCESD), where the detector takes channel estimation error and channel statistics into consideration while channel estimation is refined by detected data and considers the detection error. Based on numerical results, the model-driven DL based MIMO detector significantly improves the performance of corresponding traditional iterative detector, outperforms other DL-based MIMO detectors and exhibits superior robustness to various mismatches.

L. Liu et al. [6], concise expectation propagation (EP)-based message passing algorithm (MPA) is derived for the general measurement channel. By neglecting some high-order infinitesimal terms, the EP-MPA is proven to be equivalent to the generalized approximate message passing (GAMP), which exploits central limit theorem and Taylor expansion to simplify the belief propagation process. Furthermore, for additive white Gaussian noise measurement channels, EP-MPA is proven to be equivalent to the AMP. Such intrinsic equivalence between EP and GAMP/AMP

offers a new insight into GAMP and AMP via a unified message passing rule for non-linear processing and may provide clues toward building new MPAs in solving more general non-linear problems.

C.-H. Lee et al. [7], widely deployed Internet-of-Things (IoT) devices provide intelligent services with its cognition capability. Since the IoT data are usually transmitted to the server for recognition (e.g., image classification) due to low computational capability and limited power supply, achieving recognition accuracy under limited bandwidth and noisy channel of wireless networks is a crucial but challenging task. In this paper, we propose a deep learning-constructed joint transmission-recognition scheme for the IoT devices to effectively transmit data wirelessly to the server for recognition, jointly considering transmission bandwidth, transmission reliability, complexity, and recognition accuracy. Compared with other schemes that may be deployed on the IoT devices, i.e., a scheme based on JPEG compression and two compressed sensing-based schemes, the proposed deep neural network-based scheme has much higher recognition accuracy under various transmission scenarios at all signal-to-noise ratios (SNRs). In particular, the proposed scheme maintains good performance at the very low SNR. Moreover, the complexity of the proposed scheme is low, making it suitable for IoT applications. Finally, a transfer learning-based training method is proposed to effectively mitigate the computing burden and reduce the overhead of online training.

N. Samuel et al. [8], consider multiple-input-multiple-output detection using deep neural networks. We introduce two different deep architectures: a standard fully connected multi-layer network, and a detection network (DetNet), which is specifically designed for the task. The structure of DetNet is obtained by unfolding the iterations of a projected gradient descent algorithm into a network. We compare the accuracy and runtime complexity of the proposed approaches and achieve state-of-the-art performance while maintaining low computational requirements. Furthermore, we manage to train a single network to detect over an entire distribution of channels. Finally, we consider detection with soft outputs and show that the networks can easily be modified to produce soft decisions.

N. Jiang et al. [9], considers a low-complexity iterative linear minimum mean square error (LMMSE) multiuser detector for the multiple-input and multiple-output system with nonorthogonal multiple access (MIMO-NOMA), where multiple single-antenna users simultaneously communicate with a multiple-antenna base station (BS). While LMMSE being a linear detector has a low complexity, it has suboptimal performance in multiuser detection scenario due to the mismatch between LMMSE detection and multiuser decoding. Therefore, in this paper, we provide the matching conditions between the detector and decoders for MIMO-NOMA, which are then used to derive the achievable rate of the iterative detection. We prove that a matched iterative LMMSE detector can achieve the optimal capacity of symmetric MIMO-NOMA with any number of users, the optimal sum capacity of asymmetric MIMO-NOMA with any number of users, all the maximal extreme points in the capacity region of asymmetric MIMO-NOMA with any number of users, and all points in the capacity region of two-user and three-user asymmetric MIMO-NOMA systems. In addition, a kind of practical low-complexity error-correcting multiuser code, called irregular repeat-accumulate code, is designed to match the LMMSE detector. Numerical results shows that the bit error rate performance of the proposed iterative LMMSE detection outperforms the state-of-art methods and is within 0.8 dB from the associated capacity limit.

L. Liu et al. [10], considers a low-complexity iterative linear minimum mean square error (LMMSE) multiuser detector for the multiple-input and multiple-output system with non-orthogonal multiple access (MIMO-NOMA), where multiple single-antenna users simultaneously communicate with a multiple-antenna base station (BS). While LMMSE being a linear detector has a low complexity, it has suboptimal performance in multiuser detection scenario due to the mismatch between LMMSE detection and multiuser decoding. Therefore, in this paper, we provide the matching conditions between the detector and decoders for MIMO-NOMA, which are then used to derive the achievable rate of the iterative detection. We prove that a matched iterative LMMSE detector can achieve the optimal capacity of symmetric MIMO-NOMA with any number of users, the optimal sum capacity of asymmetric MIMO-NOMA with any number of users, all the maximal extreme points in the capacity region of asymmetric MIMO-NOMA with any number of users, and all points in the capacity region of two-user and three-user asymmetric MIMO-NOMA systems. In addition, a kind of practical low-complexity error-correcting multiuser code, called irregular repeat-accumulate code, is designed to match the LMMSE detector. Numerical results shows that the bit error rate performance of the proposed iterative LMMSE detection outperforms the state-of-art methods and is within 0.8 dB from the associated capacity limit.

III. SYSTEM MODEL

MIMO in combination with OFDM is widely used nowadays due its best performance in terms of capacity of channels, high data rate and good outcome in frequency selective fading channels. In addition to this it also improves reliability of link. This is attained as the OFDM can transform frequency selective MIMO channel to frequency flat MIMO channels [8]. So it is widely used in future broadband wireless system/communications. Cyclic prefix is the copy of last part of OFDM symbol which is appended to the OFDM symbol that is to be transmitted. It is basically 0.25% of the OFDM symbol. We can say that one fourth of the OFDM symbol is taken as CP (cyclic prefix) and appended to each OFDM symbol. IFFT is used at the transmitter and FFT is used at the receiver which substitutes the modulators and demodulators. Doing so eliminates the use of banks of oscillators and coherent demodulators. Moreover the complex data cannot be transmitted as it is; therefore it is first converted to analog form which is accomplished by IFFT. It basically converts the signal from frequency domain to time domain. Prior to IFFT operation symbol mapping is performed which is nothing but the modulation block. Any of the widely used modulation techniques can be applied like BPSK, QPSK, QAM, PSK etc. Further there are higher order modulations are also available which provide more capacity at little expense of BER performance degradation. After IFFT block pilot insertion is done and then CP (cyclic prefix) is added. Figure 1 below shows the block diagram constituting MIMO and OFDM. Any antenna configuration for the MIMO can be used according to the system requirement. Higher the configuration more will be the capacity and more will be the computational complexity of the transceiver design. It is seen that in the case of estimating channel the computational complexity is increased. Mapper defines the modulation to be used. Symbol encoder takes the shape of the STBC (Space Time Block Code) if spatial diversity is to be used and it takes the shape of the demultiplexer/multiplexer if spatial multiplexing is to be used.

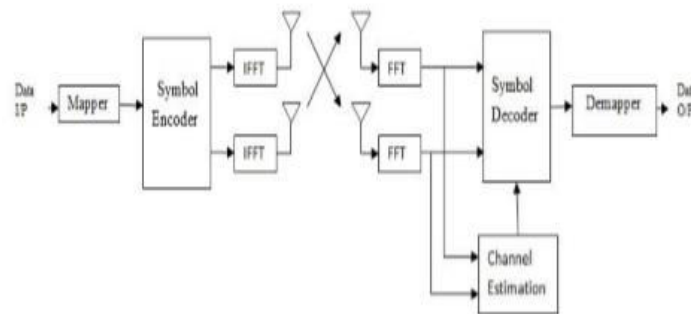


Figure 1: MIMO-OFDM system model

The received signal at j^{th} antenna can be expressed as

$$R_j[n,k] = \sum H_{ji}[n,k] X_i[n,k] + W[n,k] \quad (1)$$

Where H is the channel matrix, X is the input signal and W is noise with zero mean and variance. Also $b_i[n,k]$ represents the data block i^{th} transmit antenna, n^{th} time slot and k^{th} sub channel index of OFDM. Here i and j denoted the transmitting antennas index and receiving antenna index respectively.

The MIMO-OFDM system model [9] with N_R receives antennas and N_T transmits antennas can be given as:

$$\begin{bmatrix} Z_1 \\ Z_2 \\ \vdots \\ Z_N \end{bmatrix} = \begin{bmatrix} H_{1,1} & H_{1,2} & \dots & H_{1,N_T} \\ H_{2,1} & H_{2,2} & \dots & H_{2,N_T} \\ \vdots & \vdots & \ddots & \vdots \\ H_{N_R,1} & H_{N_R,2} & \dots & H_{N_R,N_T} \end{bmatrix} \begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_{N_T} \end{bmatrix} + \begin{bmatrix} M_1 \\ M_2 \\ \vdots \\ M_{N_T} \end{bmatrix} \quad (2)$$

Where, Z represents O/P data vector, H denotes Channel matrix, A denotes I/P data vector and M represents Noise vector. The wireless channel used is AWGN channel. After receiving the signal the CP is removed then the pilots are also removed from main signal received. After this the signal that is in time domain can be again converted to frequency domain by taking FFT of the received signal.

The sequence on each of the OFDM block is then provided to channel estimation block where the received pilots altered by channel are compared with the original sent pilots. Channel estimation block consists of the algorithms that are applied to estimate the channel.

IV. PTS SCHEMES

1. SISO PTS Scheme

In the SISO-PTS scheme, the original data sequence in the frequency domain is partitioned into M disjoint, equal length sub blocks X_v ($v = 1, 2 \dots M$) as follows.

$$X = \sum_{v=1}^M X_v \quad (3)$$

By multiplying some weighting coefficients to all the subcarriers in every subblock, we can get the new frequency sequence.

$$X' = \sum_{v=1}^M b_v X_v \quad (4)$$

Finally, at each transmitting antenna, there are $(V-1)$ sub blocks to be optimized, and the candidate sequence with the lowest PAPR is individually selected for transmitting. Assume that there are W allowed phase weighting factors. To achieve the optimal weighting factors for each transmitting antenna, combinations should be checked in order to obtain the minimum PAPR [10].

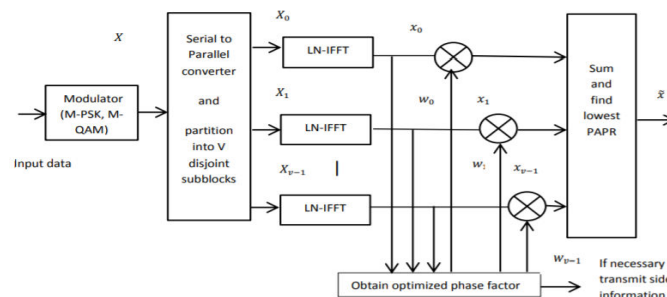


Figure 2: Block diagram of the PTS scheme with two transmit antennas

V. LEARNING BASED APPROACH

The main property of an ML is its capability to learn. Learning or preparing is a procedure by methods for which a neural system adjusts to a boost by making legitimate parameter modifications, bringing about the generation of wanted reaction. Learning in an ML is chiefly ordered into two classes as [9].

- Supervised learning
- Unsupervised learning

Supervised Learning

Regulated learning is two stage forms, in the initial step: a model is fabricated depicting a foreordained arrangement of information classes or ideas. The model developed by investigating database tuples portrayed by traits. Each tuple is expected to have a place with a predefined class, as dictated by one of the qualities, called to have a place with a reclassified class, as controlled by one of the traits called the class name characteristic. The information tuple are dissected to fabricate the model all things considered from the preparation dataset.

Unsupervised learning

It is the kind of learning in which the class mark of each preparation test isn't known, and the number or set of classes to be scholarly may not be known ahead of time. The prerequisite for having a named reaction variable in preparing information from the administered learning system may not be fulfilled in a few circumstances.

Data mining field is a highly efficient techniques like association rule learning. Data mining performs the interesting machine-learning algorithms like inductive-rule learning with the construction of decision trees to development of large databases process. Data mining techniques are employed in large interesting organizations and data investigations. Many data mining approaches use classification related methods for identification of useful information from continuous data streams.

Nearest Neighbors Algorithm

The Nearest Neighbor (NN) rule differentiates the classification of unknown data point because of closest neighbor whose class is known. The nearest neighbor is calculated based on estimation of k that represents how many nearest neighbors are taken to characterize the data point class. It utilizes more than one closest neighbor to find out the class where the given data point belong termed as KNN. The data samples are required in memory at run time called as memory-based technique. The training points are allocated weights based on their distances from the sample data point. However, the computational complexity and memory requirements remained key issue. For addressing the memory utilization problem, size of data gets minimized. The repeated patterns without additional data are removed from the training data set.

Naive Bayes Classifier

Naive Bayes Classifier technique is functioned based on Bayesian theorem. The designed technique is used when dimensionality of input is high. Bayesian Classifier is used for computing the possible output depending on the input. It is feasible to add new raw data at runtime. A Naive Bayes classifier represents presence (or absence) of a feature (attribute) of class that is unrelated to presence (or absence) of any other feature when class variable is known. Naïve Bayesian Classification Algorithm was introduced by Shinde S.B and Amrit Priyadarshi (2015) that denotes statistical method and supervised learning method for classification. Naive Bayesian Algorithm is used to predict the heart disease. Raw hospital dataset is employed. After that, the data gets preprocessed and transformed. Finally by using the designed data mining algorithm, heart disease was predicted and accuracy was computed.

VI. CONCLUSION

An extended approach cooperative and alternate partial transmit sequence named PTS was proposed for STBC MIMO-OFDM - 4G which makes uses of conjoint optimization of the PAPR for both real and imaginary parts. A high PAPR, between the two antennas, is selected to be transmitted. The proposed method performs well in terms of simulation results as well as the complexity of computation.

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