

DEEP LEARNING BASED CHANNEL ESTIMATION FOR MASSIVE MIMO

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Abstract - To improve the energy efficiency (EE) of massive multiple input multiple-output (MIMO) - orthogonal frequency division multiplexing (OFDM) systems. Orthogonal frequency division multiplexing (OFDM) is a multicarrier modulation technique for transmitting large volumes of digital but suffers high peak-to-average-power-ratio(PAPR) at the transmitter. Hadamard transform realizes precoding to OFDM signal. Low complexity detectors like Minimum mean square errors (MMSE) & Zero forcing (ZF) detectors. It is used to decrease the Bit Error Rate. To compare the overall performance of the bit error rate in OFDM system and how much amount Peak to average power Ratio in a system using Deep Learning. To improve EE, the massive MIMO-OFDM based IOT networks is given in two aspects; the downlink aspect and uplink aspect. Thus the aim is to improve BER Performance and to reduce Peak-to-Average-Ratio using PTS Scheme.

Keywords— Energy Efficiency, OFDM, PAPR, Deep Learning, BER Performance, PTS Scheme.

1. INTRODUCTION

THIRD-GENERATION (3G) wireless systems have been deployed on a broad scale around the world to provide enhanced downlink (DL) and uplink (UL) transmissions. However, due to the emerging technologies and evolving Quality of Service (QoS) requirement, future-generation wireless communication systems are expected to meet even more challenging demands of high data rate and reliable multimedia communications. As a consequence, the Third Generation Partnership Project (3GPP) has launched the long-term evolution (LTE) standard of 3G for wireless communications.

The target is to enable high speed data transmission for mobile phones and data terminals at substantially reduced compared to current radio access technologies. In order to improve the spectrum efficiency, the physical layer technologies/ specified in LTE Release 8 incorporate new techniques such as Orthogonal Frequency Division Multiplexing (OFDM) as the DL multiple access scheme and Single-Carrier Frequency Division Multiple Access (SC-FDMA) as the UL scheme. Currently, further enhancements are being studied to improve the existing LTE Release 8 standard. These enhancements are included in LTE-Advanced (also known as LTE Release 10) standard, which is targeted to support much higher peak rates, higher throughput and coverage, and lower latencies, resulting in a better user experience.

Orthogonal frequency division multiplexing(OFDM) is a multicarrier modulation technique for transmitting large volumes of digital but suffers high peak-to-average-powerratio(PAPR) at the transmitter. Hadamard transform realizes precoding to OFDM signal. Low complexity detectors like Minimum mean square errors (MMSE) & Zero forcing (ZF) detectors. It is used to decrease the Bit Error Rate. To compare the overall performance of the bit error rate in OFDM system and how much amount Peak to average power Ratio in an system using MATLAB.

2. SYSTEM MODEL

The main objective of the next generation mobile communication systems are required to support much higher variable data rate services with high quality. In direct sequence code division multiple access (DS-CDMA) mobile communication systems with time-varying multipath channels and additive [1] white Gaussian Noise(AWGN) [2] both inter-symbol interference (ISI) [3] multiple access interference (MAI) must be considered. The proposed parallel interference cancellation (PIC) receiver scheme for CP-CDMA forward link, PIC detectors use matched filter to estimate the info from all signals in parallel.

- The estimates for every user can then be wont to reduce the interference to and from the opposite signals by subtracting the estimate of every interferer from the specified user's signal.
- Ideally, this is able to allow the elimination of all interference from the specified user.
- Formally where again we have assumed perfect channel knowledge (i.e.,) Of course, in practice, this must also be estimated.

$$\hat{b}_k = sgn[y_k - \sum_{i \neq k} A_i \, \hat{b}_{i\rho_i,k}]$$

• Additionally, during this development we have assumed equal phase between the users for

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notational simplicity.

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- However, in practice we can see that there are clearly phase differences between users
- This must also be estimated and used in the cancellation process.
- In such a case, we will concede to be complex containing both amplitude and phase.
- Further, the ultimate decision statistic would need to be phase rotated before making a choice .
- Assumes the implementation of cancellation directly on the matched filter outputs.
- Since cancellation and dispreading are linear operations, we can perform cancellation prior to despreading with no change in performance.
- If cancellation is performed on the signal prior to dispreading,

$$\hat{b}_k = sgn\left[\frac{1}{T_b}\int_0^{T_b} [r(t) - \sum_{i \neq k} 2A_i \hat{b}_i a_i(t) \cos\left(\omega_c t\right)] a_k(t) \cos\left(\omega_c t\right) dt\right]$$

- Conversion of the channel into many narrowly spaced orthogonal sub-carriers render it resistant to frequency selective fading.
- Efficiently implemented using IFFT.

3. PAPR REDUCTION TECHNIQUES

3.1 Selective Mapping Method

Selected mapping (SLM) may be a promising PAPR reduction technique of OFDM system. The main idea of SLM technique is to generate a number of OFDM symbols as candidates and then select the one with the lowest PAPR for actual transmission from a number of various data blocks (independent phase sequences) that have an equivalent information at the transmitter. In the SLM method, the vectors from the first frequency domain OFDM signal are rotated supported a group of predefined phase arrays. For each signal the variant is obtained and its corresponding PAPR is evaluated.



Fig-1. Block Diagram of OFDM transmitter with the SLM Technique

- The one with rock bottom PAPR is chosen for the transmission. OFDM is a promising broadband technique. However, the implementation disadvantage of OFDM is high peak to average power ratio (PAPR)
- Selective Mapping (SLM) is an efficient method for reducing PAPR in OFDM. The main drawback of this system is that, it requires side information to be transmitted, which ends up in some rate loss.
- One among the main drawbacks of OFDM system has been its high Peak-to-Average Power Ratio (PAPR). The high PAPR brings the OFDM signal distortion within the nonlinear region of high power amplifier (HPA) and therefore the signal distortion induces the degradation of bit error rate (BER).
- Moreover, to prevent the spectral growth of the multicarrier signal within the type of intermodulation among the subcarriers and out-of-band radiation, the transmit power amplifier possesses to be operated in its linear region.
- If the HPA isn't operated in linear region with large power back-offs, it's impossible to stay the out-ofband power below the required limits. This situation results in very inefficient amplification and expensive transmitters. Therefore, it's been important and necessary to research on the characteristics of the PAPR, including its distribution and reduction, in OFDM systems, so on utilize the technical features of the OFDM.
- There have been two sorts of approaches to deal with PAPR of OFDM, one includes amplitude clipping [3], clipping and filtering [4], coding, active constellation extension (ACE) and the other one, which can be regarded as multiple signal representation technique, contains partial transmit sequence (PTS), Selected mapping (SLM), erasure pattern selection (EPS) and interleaving.
- The latter type is also called probabilistic method, and attracts most of the attention. The character of this kind of methods is not to eliminate PAPR completely, but to reduce the probability of its occurrence.
- Selected mapping (SLM) is one of the probabilistic methods with good performance in PAPR reduction. In traditional SLM, the data block is rotated by a set of different phase sequences and generates candidates with the same size and information. The candidate with rock bottom PAPR is chosen for transmission.

3.2 PTS Scheme

The disadvantage of Orthogonal Frequency Division Multiplexing (OFDM) is high Peak-to- Average Power Ratio (PAPR). Designing High Power Amplifiers (HPA) with high peaks is very difficult in manufacturing which becomes



costlier and complex. Voluminous PAPR reduction techniques have been proposed in which the present technique is Partial Transmit Sequences (PTS) with finest PAPR reduction. In this paper the evaluation of OFDM system, Precoded PTS OFDM system with assorted precoding methods like Discrete Fourier Transform (DFT) Precoded PTS OFDM, Discrete Hartley Transform (DHT) Precoded PTS OFDM, and Walsh- Hadamard Transform (WHT) Precoded PTS OFDM for M-QAM is scrutinized for enhanced PAPR reduction.

In wireless and mobile communications, due to the ever increasing technology, the information rate of the signal rises. In Orthogonal Frequency Division Multiplexing (OFDM), the vast data is split into low rate and these low data rate signal is moderated with N orthogonal subcarriers. OFDM is extensively expended in Digital Audio Broadcasting(DAB), Digital Video Broadcasting(DVB), Wireless LANs, Digital Subscriber Lines(DSL) as it has elevated power and spectral efficiency. OFDM is a multicarrier system, aches with high PAPR, degrades the proficiency of high power amplifiers (HPA). Voluminous PAPR reduction techniques have been implemented like distortion based techniques: clipping trail to in-band and out-band distortion and Companding demoting the out-band distortion and BER which are not power efficient and some probabilistic techniques like selected mapping method(SLM), partial transmit sequence(PTS) were implemented. The subcarriers of OFDM signal is used by generated correlated signals. In PTS the multiplication and additional complexity can be lowered by using less IFFTs. To get considerable PAPR of OFDM signal the subcarrier waveforms are biased with different shapes.



Fig-2 Block Diagram of OFDM System with PTS Scheme

The precoding methods are distortion-less, amplifies the diversity gain and degrades PAPR. In this fostered technique the Precoding methods like Discrete Fourier Transform (DFT), Discrete Hartley Transform (DHT), and Walsh Hadamard Transform (WHT) is spread over the PTS OFDM system. Let us consider N parallel subcarriers which are used to transfer the signal,X=Xk, k{0,1.....N}.

The N subcarriers are orthogonal and are stored within the time interval T. Each symbol is used to modulate with one of the subcarriers and at last all modulated signals are transferred simultaneously over the time interval T. Each symbol is made on IFFT operation. The OFDM system assuming the signal consists of real and imaginary parts which are in frequency domain and converted into time domain by IFFT/IDFT. Calculating PAPR for continuous time signal is difficult therefore estimating PAPR for discrete time is same as continuous time by oversampling the signal L times.

3.3 Constant Modulus Algorithm

CMA has the assumptions that input to the channel is a modulated signal which has constant amplitude at every instant in time. The advantage of the blind equalization is that the bandwidth is high due to there's no training of the pulses. In the conventional equalization process needs the training of the heart beat. CM is used for QAM signals where the amplitude of the modulated signal is not the same at every instant.

- The error e(n) is then determined by considering the nearest valid amplitude level of the modulated signal as the desired value. Adaptive channel equalization without a training sequence is understood as blind equalization. A baseband model with a channel impulse response, channel input, additive white Gaussian noise (AWGN), and equalizer input are denoted by c(n),s(n), w(n), and u(n) respectively.
- The data symbols transmitted s(n), are assumed to consist of stationary independently and identically distributed (i.e.), real or complex non-Gaussian random variables.
- The equalizer input, u(n)=s(n)*c(n)+w(n)
- Constant modulus algorithms (CMAs) experience significant recognition as methods for blind supply separation and equalization of verbal exchange signals. As a regular software, take into account a wireless situation in which a number of customers are broadcasting indicators at the equal frequency on the same time. The alerts acquired at a base station can be a few superposition of the transmitted sources.
- If the bottom station is equipped with more than



one antennas, then it is possibly that each antenna will acquire a exceptional combination of the alerts. By linearly combining the antenna outputs, the goal is to split the alerts and to obtain every of them at the same time as suppressing interference from the other signals.

• The challenge of the blind beam former is to compute the proper linear combos from the measured information only, without distinctive information of the alerts or the channel. Mathematically, the state of affairs is described by means of the easy and well-known statistics version (after sampling and baseband conversion).



- where the vector x(k) may be a stacking of the m antenna outputs xi(k) at discrete time k,
- s(k) may be a stacking of the d source signals si(k), and A is that the array response matrix which describes the linear combinations of the signals as received by the antennas. This model is a reasonably accurate description for stationary propagation environments in which the multipath has only a short delay spread (as compared to the inverse of the signal bandwidths), so that no equalization is required.
- The beamforming problem is to find weight vectors wi, one for each source, such that w* i x(k) = si(k) is equal to one of the original sources, without interference from the others. (* denotes a complex conjugate transpose.) Equivalently, we try to find A and then a pseudo-inverse of it such that W*A = I. The columns of W are equal to the w.
- Although we are able to be involved with blind beamforming, it is beneficial to note that a pretty comparable hassle arises within the context of blind equalization of a single source determined through an unknown time-dispersive FIR channel. In that situation, the acquired signal x(ok) is a linear combination of shifts of the unique source s(k).
- The feeding x(ok) thru a tapped postpone line, we are able to assemble a vector of acquired alerts and we are able to arrive at the identical version as (5.1.1), be it with greater structure given that si(okay) = s(ok-i) and xi(ok) = x(k-i). Another issue that distinguishes blind equalization from blind beamforming is that inside the latter we strive to receive all independent assets. Originally, maximum blind beamforming algorithms had been that specialize in properties of A For instance, direction finding algorithms expect that the columns of A are vectors on the array manifold, each related to a sure

route-of-arrival (DOA). By locating those instructions, we attain an estimate of A, and subsequently we can construct a beamformer W to separate the assets. This technique calls for a calibrated array, and a scenario with very limited multipath propagation (considering all DOAs should be predicted).

4. SIMULATION RESULTS

4.1 Selective Mapping Method



4.2 PTS Scheme



4.3 Constant Modulus Algorithm



5. CONCLUSIONS

OFDM channel estimation method for the mmWave massive MIMO systems. Hadamard transform realizes precoding to OFDM signal. Low complexity detectors like Minimum mean square errors (MMSE) & Zero forcing (ZF) and is used to decrease the Bit Error Rate. The overall performance of bit error rate and the amount of peak to average power ratio is compared by using Deep Learning. Our results show that OFDM can achieve improved BER performance for different noise levels. Its effectiveness, flexibility and efficiency, OFDM can be used as a practical solution for channel estimation in mmWave massive MIMO systems. The Peak to average power ratio is reduced using PTS scheme.

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