Deep Learning based OFDM System for Underwater Acoustic Communication with Mitigation of Peak to Average Power Ratio

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Abstract— The need of fast, reliable and the accuracy in communication networks is increasing day by day. The intelligent networks have left their beneficial impact in underwater acoustic (UWA) orthogonal frequency divisional multiplexing (OFDM) communication system. In the UWA communication network the OFDM technology is employed to get a reliable and robust communication. For obtaining better performance of bit error rate (BER) and significant gain in the system, the deep learning auto-encoders are utilized in deep neural networks (DNN). Considering several benefits of auto-encoders in the OFDM system it goes through high peak to average power ratio (PAPR) that makes power amplifier (PA) operating in nonlinear region. So, to maintain the operation of power amplifier working in linear region, this paper proposes a deep learning based PAPR mitigation method termed as T-AE, PAPR method. Firstly, the PAPR is reduced with a novel T-AE layer in the auto-encoder; secondly the proposed method makes the PA operate in the linear region. Finally, to prove the feasibility of proposed method the simulation is performed which verifies the superiority of our proposed method with efficient performance of BER as compared to traditional OFDM systems.

Index Terms— OFDM, PAPR, Auto-Encoder, Tanh layer.

1 INTRODUCTION

THE development of high data transmission through wireless communication system is increasing day by day. Till now OFDM is fastest and is considered as the solution to huge data transmission according to the growing need of mobile users. The OFDM technique is used in 3rd generation and 4th generation because of several advantages. After establishment of successful radio communicating networks using OFDM, the researchers have also implemented the scheme for communication between underwater networks. Though OFDM is considered as long-range scheme with fastest responding to user's request and high bit data stream, but still observe PAPR problem, which is mainly caused by the two successive crests coincide at the same point. The difference in underwater and terrestrial communication system is of communication signal. As only Acoustic signal (voice signal) has good results in the underwater. To solve the PAPR problem, many PAPR reduction techniques have been proposed in the literature.

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On the hand Deep Neural Networks (DNN) have many applications in wireless communication such as, designing the constellation at transmitter, estimating the channel, information searching and also used when the information is decoded at receiver side [1-3]. The DNN provides significant gain and energy efficiency in the wireless communication and they are also the best solutions for complex heterogeneous intelligent communication networks [4, 5]. The auto-encoder (AE) is mostly used now a day for layout designing of any wireless communication networks, which is the also an application of DNN. The trained auto-encoders send the inputs to outputs in the compressed form, and then input containing information can be recovered at receiver[5, 6]. The model contains encoder and decoder for compressing and decompressing operations respectively. The use of auto-encoders in the wireless communication resolve the detection and classification issues[7-9].

In [10, 11] the authors have proposed a de-noising auto-encoder for the modulation classification. In [12]the authors have trained the auto-encoder by convolutional method for modulation basis function used in the radio signals. To construct an end-end wireless communication network, auto-encoders were being observed [13]. The encoders are designed to represent the transmitters and decoders for receivers. The set of inputs at transmitter side is called transmitted set of symbols, while the set of outputs are termed as set of received output symbols. The classification problem occurs while reconstructing the input symbols at receiver side. The set of input symbols contains 1s and 0s. The end to end communication system based on auto-encoders is much improved because the loss function is much reduced. And for reducing loss function, the auto-encoders don't require prior knowledge of transceivers. These methods are used to get good BER performance in the communication network, the auto-encoders used in end to end wireless communication systems still suffers peak to average power ratio (PAPR) problem, which is high at transmitting signals [14-17]. This is

produced when the peaks of some signals coincide at one point that result higher peaks. So, the peaks power is much higher than average power.
When higher peaks are fed to power amplifier will lead power amplifier into saturation region, and affects the performance communication system, hence the efficiency is decreased [18, 19]. The high PAPR in auto-encoders based communication system is because of normalized layer in the architecture of auto-encoders, in which unit average power is the requirement and also approximately Gaussian distribution. The maximum transmitted signal is, therefore, closely related to the expansion of a Gaussian distribution tail resulting in a high maximum transmitted power [20-24]. Adding PAPR with loss function is the only proposed solution for the reduction of PAPR in auto-encoder based end to end communication system [25, 26]. The same method is used for mitigation of PAPR in the optical OFDM communication system[27].

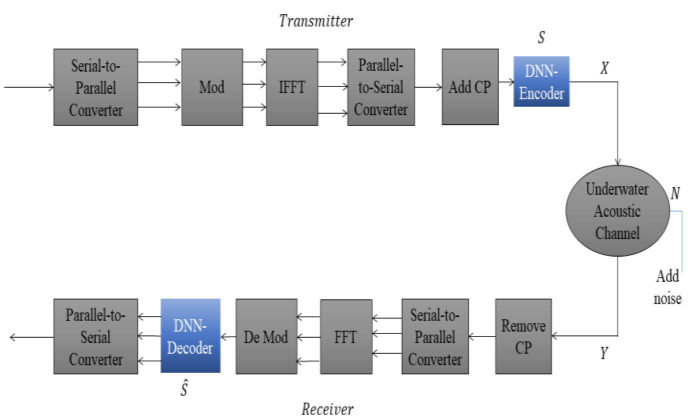

Fig. 1. Block diagram of proposed DNN-autoencoder in UWA OFDM system

It is observed that by adding loss function becomes the reason of trade-off between BER and PAPR which may lead to low BER performances.
In this paper, we have proposed a deep learning based PAPR reduction method in the underwater and acoustic environment using auto-encoders. The PAPR is much reduced as compared to conventional schemes as a layer of 'tanh' is added to observe the performances, we named this T-AE PAPR method. Moreover, the normalization power is being shifted outside of deep learning network. By doing this the higher peaks levels are controlled by auto-encoders, so the loss function can be described easily on the basis of BER. In the conventional methods adding loss function with PAPR, in which performances of BER can is observed. Here, we have added 'tanh' layer and without adding loss function to get improved performance. In the end, both models are compared, and it is proved that our proposed T-AE PAPR outperforms the AE based DNN with marvelous performance of BER.

2 System Model

The basic communication model of underwater OFDM using encoder and decoder is shown in given figure 1. The input symbols are denoted by $s \in \mathcal{M} = \{1, 2, 3, .., M\}$, here $M = 2^c$ represents the length of symbols, and k is the reserved bits for information. One input symbol is being selected by transmitter, then mapping $f: \mathcal{M} \to \mathbb{R}^n$ is done for the generation of the signal X that will be sent towards receiver end. The transmission rate can be given as,

$$R = \frac{k}{n} \tag{1}$$

Where n is the number of channels used. The generated signal X is then transmitted to BELLHOP channel. The output at receiver is denoted by Y,which can be understand from given equation,

$$Y = X + N \tag{2}$$

Here N is the noise in the channel, and the mapping $g: \mathbb{R}^n \to \mathcal{M}$ is applied by receiver so as to recover the symbol [13].

2.1 Autoencoder Network

In the network of auto-encoder the generated signals are transmitted in forward simply in the compressed form and it is also termed as feed-forward neural network. The compression of signals is done by encoder and decompression is done by decoder to recover the source signals. The encoder and decoder perform the operation approximately equal to linear, and can be written in semi-linear vector forms as,

$$f(s; w_1): \mathbb{R}^M \to \mathbb{R}^n \quad function\ 1 \tag{3}$$

$$g(t; w_2): \mathbb{R}^n \to \mathbb{R}^M \quad function\ 2 \tag{4}$$

Here s is the input to encoder and t is the input to decoder, while $w_1$and w_2 are the weights of inputs. The process starts with input s to encoder to form $f(s; w_1)$, and then this output of encoder then passed through decoder to achieve the recovered source form and it is illustrated as,

$$g(f(s; w_1); w_2) \tag{5}$$

Here, the purpose of auto-encoder is to recover source form (input data) by reducing the loss function, which is given as,

$$L(s, g(f(s; w_1); w_2)) \tag{6}$$

The loss function also defines the difference between source data (input) and output data. To recover source data, a lot of loss functions are used depending upon the properties of input s. As the input here is taken a hot vector, in which all elements are zero except one element, and it is called class-1 vector. And hence binary classification problem is observed when the decoder tries to classify this form of input s, which is given in equation 1. For binary classification, the loss function can be given as,

$$L(s, g(f(s;\ w_1);\ w_2)) = \big[s log(g(f(s;\ w_1);\ w_2)) + (1 - s)\log\big(1 - (g(f(s;\ w_1);\ w_2))\big)\big] \tag{7}$$

Moreover, stochastic gradient descent (SGD) is applied using Adam optimizer for finding the suitable weights of auto-encoder which is expressed as,

$$w := w - \gamma\, \nabla_w\, L(s, g(f(s;\ w_1);\ w_2)) \tag{8}$$

In above equation, w represents the weights, which is the transpose matrix can be written as $w = [w_1{}^T w_2{}^T]$, the rate of learning can be denoted by γ, and gradient with ∇w.

2.2 Applications of Auto-encoder in Communication systems

The auto-encoder are mainly used in today's end to end wireless communication systems, where encoders are considered as transmitters and decoders are regarded as receivers. Figure 2 illustrates the block diagram of auto-encoder in the end to end communication system. There are three different layers in transmitter, receiver and channel, which are dense, normalized and a noisy layer for channel. The layers at transmitter side are Dense + ReLU, Dense + linear, and Normalization, which have dimensions of output a M, M, n and n. The channel contains only one layer of noise with dimension n. The receiver contains two layers namely, "Dense + ReLU" and "Dense + softmax" with dimension given as M, M. The probability of input message (attempting message) to transmitter is M symbols, which is known as one hot vector, and can be represented as $1_s \in \mathbb{R}^{\mathrm{M}}$, the s^{th} element is the only non-zero and considered as 1. The data bit stream carried by input message is fed to the first layer of transmitter, in which encoder is placed, the data is encoded to generate X signal, which is the formation of real numbers, where n denotes the channel number. The process follows the same scenario as the conventional OFDM wireless communication is modeled; such that data bit stream is being transmitted to channel after modulation. But in this auto-encoder model the average power of signal should be one, which is done by normalization layer. Then, the signal is allowed to pass through BELLHOP channel, having multipath, several delays. Finally, the signal is received at the hydrophone and becomes Y. The decoding operation is done by decoder placed at receiver end. The activation function Soft-max is applied at the last layer in the decoder, so the vector size of output network is probably being M.

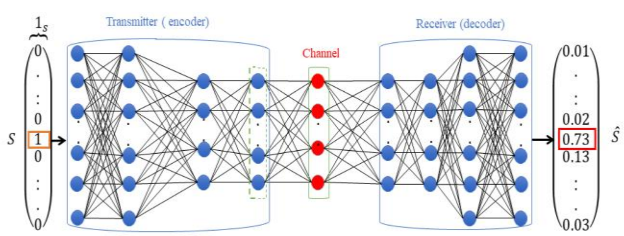

Fig. 2. Proposed PAPR reduction method based on auto-encoder in UWA OFDM system

3 Proposed Model

In the proposed model we consider reducing the PAPR, so the PAPR mitigation is discussed firstly in end to end UWA communication system, where auto-encoders are being implemented. After looking at the various advantages of auto-encoder, a drawback of high PAPR is also observed, which leads to poor performance of overall communication system. Hence, it should be softened to minimum value. The PAPR can be defined as the ratio of maximum power to average power. Generally, the PAPR is given as,

$$PAPR\{X\} = \frac{max\{|X[i]|^2\}}{E\{|X|^2\}}, \quad 1 \le i \le n \tag{9}$$

Here $E\{.\}$ is the expectation operator, and n defines the channel number. In the section II, the layers of normalization are used, which makes the power distribution not proper of all the transmitting signals, and considered approximately to the Gaussian, and the average power is taken 1. The high PAPR is resulted in OFDM systems, when the maximum transmitted power is expanded with addition part called tail, which is equal to Gaussian distribution. There are many methods, which have been proposed for reduction of PAPR in the literature. But in the auto-encoder based intelligent communication system, the method of adding PAPR with original loss function is discussed by only very few researchers in which the system is controlled by its coefficient [27]. It is given as,

$$L(s, \hat{s}) = L_1(s, \hat{s}) + \eta L_2(s) \tag{10}$$

Here L_1 defines the amount of BER degradation, L_2 is the amount of PAPR, while η is the PAPR controlling coefficient, and it also determines the effect on loss function. One drawback of this method is the selection of coefficient η; we can either have good PAPR or good BER. By changing the value of coefficient, it may lead to sacrifice one of the performances. We can observe that the value of PAPR is dependent on the value of k, by increasing the value of k, the PAPR will be increased. Due to high PAPR, the overall performance will be decreased, so this method is not appropriate for high rate of situations. After considering all these situations, we have proposed our model names as PAPR reduction in auto-encoder consisting of $tanh$ layer. It is learned through DNN and discussed in the training portion.

3.1 PAPR Reduction in Auto-encoder

Figure 2 illustrates the block diagram of PAPR reduction scheme which is totally based on auto-encoder of DNN. Referencing [13]and [27]normalization layer is added, but we have added another layer instead of using normalized layer. The additional layer can be seen in red dotted lines, which is the main control unit to maintain the peaks i.e. controls the PAPR, by using tanh function, and that will be another new layer in the auto-encoder model. The concept can be well understood by Gaussian distribution of the transmitting signal. If the distribution is Gaussian, then majority of the power can be seen around the mean of transmitting signal, which raises the PAPR. So, the expanded part (tail) of distribution should be limited to reduce the maximum transmitting power, and average transmitting power should be kept constant. It is observed that the PAPR is reduced by doing this. Further we are using a function α tanh(βx), so proper tuning is required, i.e. tuning of α and β. With the help of this, PAPR as well as BER performances can be improved up to optimal results.

3.2 Training

The transmitting power will not be equal to one by replacing the normalized layer with another layer. But to reduce noise of the channel, that the signal faces, the network tries to increase the transmitting power. And the network gives priority to increase power and training the auto-encoder to lean features of channel will be the done later. So, it is recommended to have end to end communication, so the learning issue will be resolved, following method is used in the training process:

1. The noise is constant while training the network as shown in figure 2. When the network is trained, the part of encoder with learned weights is separated.
2. In the second step we have added a new noise layer in the network above used in the first step, and then keeping values of weights constant, now the training is done so as to find the new weights which are optimum requirement for decoder of the network.

In the second step, if we fix the weights of encoder, then average transmitted power will also be fixed. By keeping the encoder weights fixed during the second step, the average transmitting power is forced to remain fixed during the training procedure. The same way the network can be trained by adding the required noise. After second step the network learns the parameters of the channel, and average transmitted power will also be constant.

4 Results And Discussion

In this portion the simulation is performed for the proposed method. We will discuss the performance of our proposed model on simulation basis by employing MATLAB 2018a. After taking random values of M and n, representing the number of symbols and channel. The proposed model is trained over 100000 samples using BELLHOP ray tracing channel by creating ENV file and giving the sound speed profile which is between 1480m/s to 1505m/s. The transmitting transducer (TX) is kept 5m in the water and the depth of hydrophone (RX) is 8m. The distance between TX and RX is 3km. The other parameters in the simulation were taken as the training rate of 0.001, and Eb/N0 is equal to 7dB, which constant for whole process. The auto-encoder is trained by above mentioned leaning method.

Figure 3 represent the linear response of the power amplifier. It can be seen from the figure that the PA is operating linearly, and the non-linearity is mitigating to full of extent in our proposed method. Figure 4 exhibits the PAPR performance of communication system. The CCDF of PAPR is used as performance metric to measure the PAPR. It can be observed from the figure that the PAPR of original signal is 11.4Db. It is compared with the traditional PAPR reduction methods such as Clipping, partial transmit sequence (PTS) and L-AE, PAPR. In the end, the proposed T-AE PAPR reduction scheme outperform than the conventional schemes i.e., 6.2db.

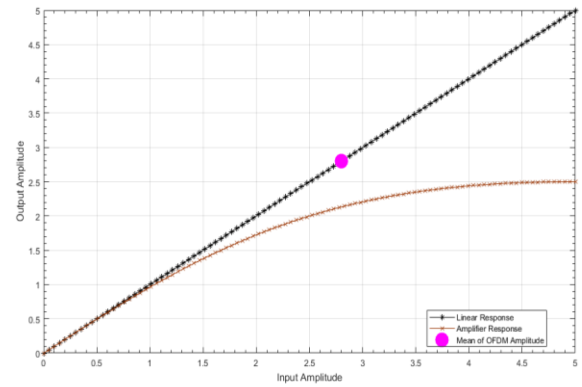

Fig. 3. Linear response of power amplifier

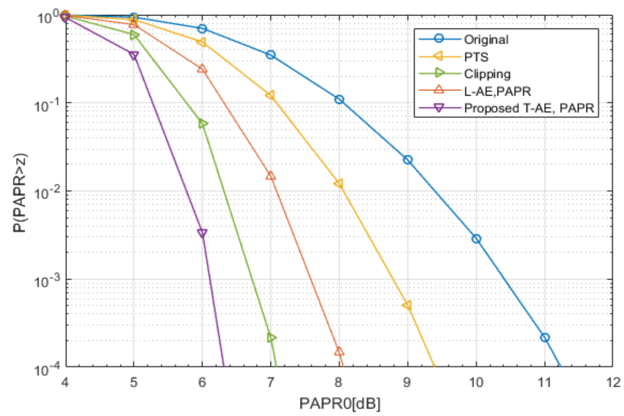

Fig. 4. PAPR representation of Proposed T-AE PAPR scheme

Figure 6 represents the BER comparison of proposed 'tanh' layer added in autoencoder based PAPR reduction scheme with Loss function auto encoder PAPR method and original signal. By taking different number of Eb/N0 the architecture of our proposed scheme is illustrated with improved performance. The values of n and k were 7 and 4 respectively with binary modulation that supports values of n and k for correction to build a code to auto correct the errors. Here, the batch is 300 for 3 architectures. The epoch numbers are set to 65 and 17 for learning curves. We need to do fine tuning of α and β to get closer performances to actual auto-encoders. The η is fine tuned for L-PR-AE, but the proposed Tanh – based PAPR method has more reduction of PAPR performances, with good BER results. Finally, we can see in the fig 5, we have better and improved BER results than conventional techniques

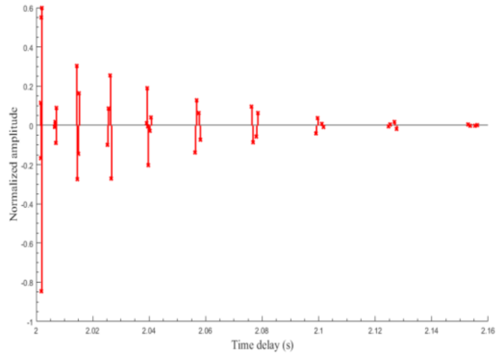

Fig. 05. Channel Impulse Response at distance of 3 KM.

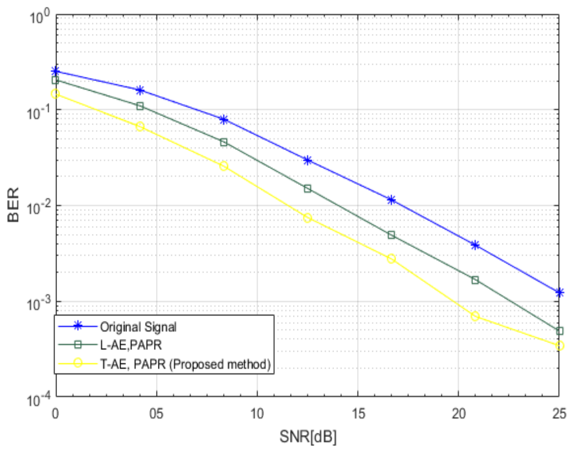

Fig. 6.BER performance of Proposed scheme with Loss added auto-encoder method and conventional method

5 Conclusion And Future Work

This paper proposed a novel PAPR reduction method for underwater acoustic OFDM communication system by replacing a normalized layer with 'tanh' layer in autoencoder of deep neural network. Firstly, the PAPR is reduced by adding 'tanh' layer in the DNN, we named this as T-AE PAPR reduction method. Secondly, this method makes power amplifier to operate in the linear region, so as to mitigate the nonlinear distortion in the overall communication system. The method was compared with AE encoder PAPR reduction method, from the comparison it is proved that the proposed method is the best solution for mitigation of PAPR, nonlinear distortion with less complexity, and energy efficiency. Finally, the simulation is performed which verifies that the bit error rate (BER) is also improved for the proposed method. In future work different types of loss functions on the DNN can be applied to check the performance of the communication system.

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