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Research article

When high PAPR reduction meets CNN: A PRD framework

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Abstract: One of the most important factors limiting the performance of OFDM (Orthogonal Frequency Division Multiplexing) system is high PAPR (Peak to Average Power Ratio). Great efforts have been made in suppressing PAPR, but their implementation often requires pre-processing all input signals, leading to excessive calculation overhead. When the transmission speed is high, much more time will be taken to process the input signal with the traditional methods, which will reduce the performance of the system. In this background, this paper firstly presents an algorithm, called PRD, to identify the high PAPR sequence without IFFT (Inverse Fast Fourier Transform) operations, in which a CNN (Convolutional Neural Network) for identifying PAPR sequences is trained first before applying further PAPR reduction schemes. Experimental results show that the proposed algorithm can identify the high PAPR sequences with 92.3% accuracy and reduce PAPR with extremely low calculations.

Keywords: convolutional neural network; orthogonal frequency division multiplexing; peak to average power ratio

1. Introduction

As the high speed transmission demand becomes more and more important with the rapid developed society, the performance of the transmitted wireless signals needs to be optimized desperately, for example, the reliability issue about the wireless communication is discussed in [1–5], where the security transmission is fully considered; and the effectiveness aspect in the communication system is critical to ensure the high efficiency of upper-layer computing paradigms [6, 7, 9–11], such as wireless edge computing and digital twin [8], in which the transmission latency is an important factor of the system design. Owing to lots of advantages of the Orthogonal Frequency Division Multiplexing (OFDM) technology, it has been widely used in multiple communications systems in the 5G vision. However, high Peak to Average Power Ratio (PAPR) can severely degrade the performance of OFDM-based communications systems, and impact the service lifespan of the system from the perspective of energy consumption. Multiple subcarriers accumulating in the same direction at a certain moment lead to a large peak value; this requires the power amplifier to have a large linear area. Otherwise, when the peak value of the signal enters the nonlinear region of the amplifier, the signal will be distorted, which would result in inter-modulation interference and out-of-band radiation between subcarriers, and destroy the orthogonality between subcarriers and degrading the performance of the system. Therefore, how to reduce the PAPR has been a great concern in the system design.

Many efforts have been made for reducing the PAPR of OFDM signals, which can be roughly divided into three categories, i.e., signal predistortion technology, coding technology, and probabilistic technology. Liu et al. proposed a method using iterative clipping to reduce PAPR based on signal predistortion technology [12]. Xu et al. proposed an unitary precoder algorithm to reduce PAPR based on coding technology [13]. Mata et al. proposed an improved Partial transmission sequence (PTS) algorithm to reduce PAPR with probabilistic technology [14]. As far as the above research is concerned, even though the signal predistortion technology is simple and direct, it will bring in-band noise and out-of-band interference, and reduce the system's bit error performance and spectral efficiency. Despite the coding technology will not distort the signal, it is very complicated to realize. Besides, since the information rate decreases faster than coding, the coding method is only applicable to the case where the number of subcarriers is small. In addition, note that probabilistic technology will not distort the signal, which can effectively reduce the PAPR of the signal, but the computation complexity is too high.

Despite lots of efforts have been made in the PAPR reduction, however, in the high speed transmission scenario, they all need to operate the IFFT (Inverse Fast Fourier Transform), which will lead to the extra calculation time and decrease the transmission speed. Therefore, based on the consideration of feasibility and robustness from the above analysis, a promising method to reduce PAPR is the probabilistic technology with low computation complexity. To our best knowledge, current probabilistic techniques for PAPR reduction all reduce the PAPR of the entire input signal sequence. In other words, they apply PAPR reduction method directly without detecting PAPR. On the other hand, SVM (Support Vector Machine) algorithm and traditional neural network algorithms are not as good as CNNs (Convolutional Neural Networks) in detecting high PAPR sequences [11,15,16]. In this paper, we adopt CNN to identify high PAPR sequences, and then in combination with the PTS algorithm, the identified high PAPR sequences are reduced at last. In addition, our main contributions in this paper are threefold:

- To our best knowledge, this is the first paper that applies CNN to identify high PAPR sequence before reduction in the OFDM-based communication systems, where the number of IFFT operations are greatly reduced and the transmission speed is promoted.
- The presented algorithm can reduce the calculation complexity of the RAPR reduction system to a great extent, which can be applied in the high speed data transmission scenario.
- Without plenty of IFFT operations, the proposed algorithm can identify the high PAPR sequences with a probability of 92.3% in typical parameters settings.

The remainder of this paper is organized as follows. Section II describes the system model in the PAPR reduction problem. The identification algorithm is introduced in section III. Simulations and results analysis are detailed in section IV; and section V briefly concludes the paper.

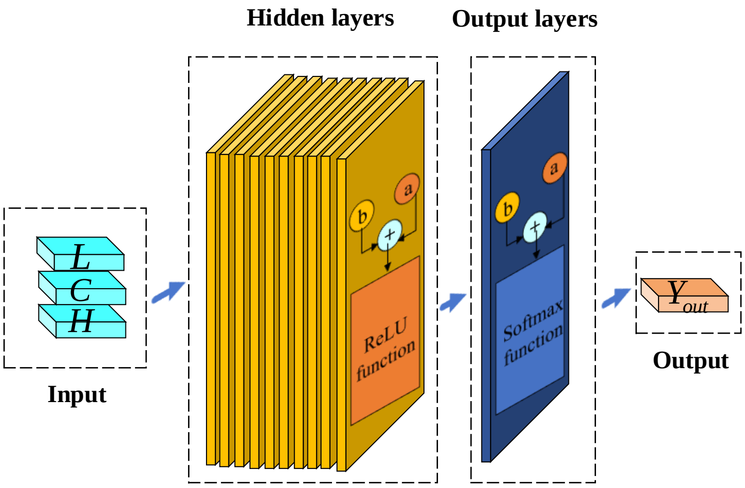


Figure 1. Construction of CNN.

2. System model

2.1. OFDM system and PAPR

We assume there are N independent and modulated symbols in the OFDM symbol block ,which can be expressed as $X = [X_0, X_1, \dots X_{N-1}]^T$, and X_K represents the symbol modulated by k-th subcarrier. When the OFDM symbol makes N points IFFT, the discrete time OFDM signal $x = [x_0, x_1, \dots x_{N-1}]^T$ can be denoted as (2.1).

$$x_n = \sum_{n=0}^{N-1} X_K e^{j2\pi nk/N}. \tag{2.1}$$

Besides, PAPR represents the ratio of the maximum power value to the average power value in an OFDM symbol, which can be calculated as (2.2).

$$PAPR{=}10\log_{10}\frac{\max\left\{|x_n|^2\right\}}{E\left\{|x_n|^2\right\}}\ dB\cdot \tag{2.2}$$

In order to describe PAPR intuitively, the CCDF (Complementary Cumulative Distribution Function) is adopted here to measure the distribution of the signal's PAPR. The physical meaning of the CCDF is to calculate the probability that the PAPR value exceeds a certain threshold $PAPR_0$, which is expressed as (2.3).

$$CCDF = \Pr(PAPR > PAPR_0)\cdot \tag{2.3}$$

2.2. Construction of CNN

As shown in Figure 1, define the data of each OFDM symbol block at the input as three dimension data G, which is composed of the modulation type L, the number of sub-carriers C, and the hash value H of the corresponding sequence in the OFDM symbol. At the same time, G can also be divided as high PAPR sequences G_{HP} and non-high PAPR sequences G_{NH} as (2.4).

$$G = [L|C|H]^T = [G_{HP}|G_{NH}]\cdot \tag{2.4}$$

Since the sample numbers of G_{HP} and G_{NH} in the input data differ greatly, it is difficult to directly train the CNN with raw samples where the data is unbalanced [11]. According to [11], the method of balanced down sampling is used here to process the input data G_{NH}. Define f_s as the function to calculate the number of sample data, and r_i represents the ratio of the number of samples of the high PAPR sequence to the i-th down-sampled non-high PAPR sequence in (2.5).

$$r_i = \frac{f_s\left(G_{HP}\right)}{f_s\left(G^{(i)}{}_{NH}\right)} \quad (1 \le i \le e) \cdot \tag{2.5}$$

Besides, as shown in (2.6) and (2.7), $M^{(i)}$ represents the i-th input data composed of the high PAPR sequence and the i-th down sampled PAPR sequence, w_i is the weight of the i-th input data, where the number of down-sampled data is e.

$$M^{(i)} = \left[G_{HP}|G^{(i)}{}_{NH}\right] \cdot \tag{2.6}$$

$$w_i = \frac{r_i}{\sum\limits_{i=1}^{e} r_i} \cdot \tag{2.7}$$

After down sampling the unbalanced data, we use the i-th data as input data to train the CNN network. Here, the number of hidden layers is set as 10, and the output layer number is 1, the weight of the i-th hidden layer is $A_R{}^{(i)}$, the bias value is $B_R{}^{(i)}$, the weight of the output layer is A_S, the bias value is B_S, the function of the hidden layer is f_R in (2.8), the output layer's function is f_S in (2.9).

$$y_R = f_R\left(\sum_{i=1}^{10} M^{(i)} \cdot A_R{}^{(i)} + \sum_{i=1}^{10} M^{(i)} \cdot B_R{}^{(i)}\right) \cdot \tag{2.8}$$

$$y_s = f_S\left(A_S \cdot y_R + B_S \cdot y_R\right) \cdot \tag{2.9}$$

The output of the hidden layer is denoted as y_R , y_S represents the output of the output layer, and the weighted output result of all samples is y_{out}, which is of one dimension as shown in (2.10).

$$y_{out} = \sum_{i=1}^{e} w_i \cdot y^{(i)}{}_s \cdot \tag{2.10}$$

3. PAPR reduction in OFDM

As shown in Figure 2, assume that there are D sequences to be transmitted, which is denoted as X_{in} in (3.1), the number of subcarriers is c, and $x'_i = \{x_{i1,}x_{i2,} \ldots x_{ic}\}$ is a column vector. Therefore, the sequence after serial-to-parallel conversion can be expressed as X_{sp} in (3.2), and the symbol block can be denoted as X_b in (3.3). Besides, the hash value of the i-th symbol block can be calculated by (3.4).

$$X_{in} = \left\{x_{ij}|1 \le i \le c, 1 \le j \le \frac{D}{c}\right\} \cdot \tag{3.1}$$

$$X_{sp} = \left\{x'_i|1 \le i \le \frac{D}{c}\right\} \cdot \tag{3.2}$$

$$X_b = \left\{x''_i|1 \le i \le \frac{D}{m \cdot c}\right\} \cdot \tag{3.3}$$

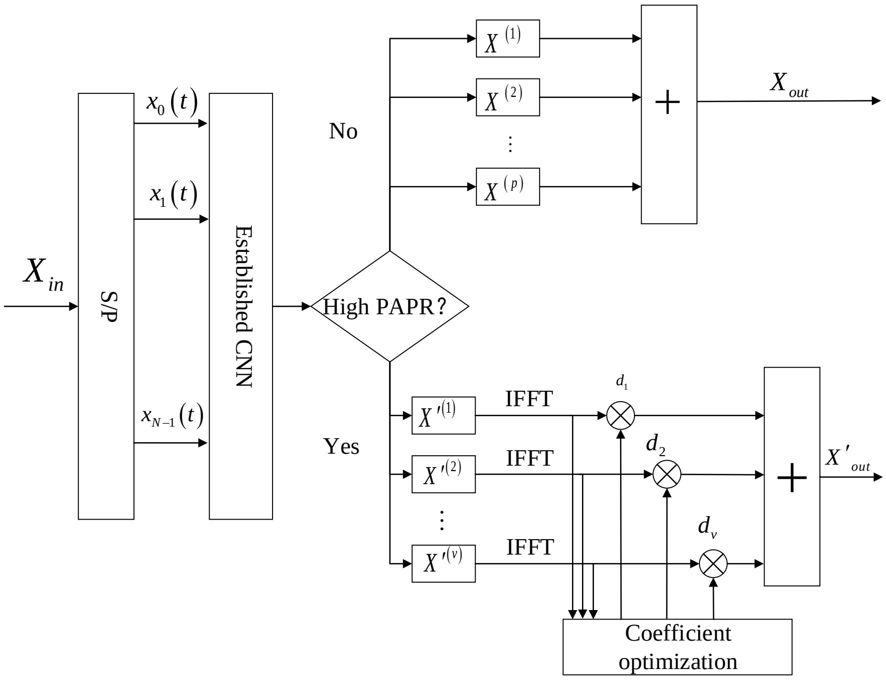


Figure 2. The flow to reduce PAPR in OFDM with proposed algorithm.

$$H_b^{(i)} = \sum_j \sum_i 2^{x_{ij}} \left(x_{ij} \in X_b \right) \cdot \tag{3.4}$$

Define the function of CNN to identify the PAPR as $f_c^{(i)}$in (3.5). When the output of CNN y_{out} is larger than the decision threshold β, record the output of $f_c^{(i)}$ as 1, and vice versa as 0. Among them, the sequence with the decision result of 0 represents the non-high PAPR sequence, a sequence with a judgment result of 1 indicates a high PAPR sequence. For p non-high PAPR sequences, we directly output them as (3.6).

$$f_c^{(i)} \left(c, m, H_b^{(i)} \right) = \begin{cases} 1 & y_{out} \geq \beta \\ 0 & y_{out} < \beta \end{cases} . \tag{3.5}$$

$$X_{out} = \sum_{i=1}^{p} X^{(i)}. \tag{3.6}$$

For the detected high PAPR sequences, due to their small number, PTS method is used to process them here. Assume that there are v high PAPR sequences which need to be processed with PTS method. Firstly, perform IFFT on them according to (3.7), and then appropriately selecting the rotation vector factor d to satisfy (3.8), so that the peak signal at this time reach the best. After optimizing the coefficients of (3.8), we perform PTS on high PAPR sequences according to (3.9), thereby reducing the PAPR of the system.

$$x'^{(v)}{}_{PTS} = IFFT \left(X'^{(v)}{}_{PTS} \right) \cdot \tag{3.7}$$

$$\{d_1, d_2, \ldots d_v\} = \underset{\{d_1, d_2, \ldots d_v\}}{\arg\min} \left(\max_{1 \leq n \leq N} \left| \sum_{v=1}^{V} d_v x'^{(v)}{}_{PTS} \right|^2 \right) \cdot \tag{3.8}$$

$$X'_{out} = \sum_{v=1}^{V} d_v \cdot x'^{(v)}{}_{PTS} = \sum_{v=1}^{V} d_v \cdot IFFT\left(X'^{(v)}{}_{PTS}\right). \tag{3.9}$$

Based on the above analysis, a CNN-based algorithm for PAPR reduction with detection in OFDM systems is proposed here. As shown in Algorithm 1, in the offline stage, the CNN for identifying high PAPR sequence is trained, and the PAPR reduction is performed according to the result of offline stage in the online stage.

Algorithm 1 PAPR Reduction with Detection in OFDM (PRD)

Offline stage

Input: Each OFDM symbol block G

Output: Established CNN

1: **For** G **do**
2: Determine L,C and H based on (2.4)
3: Derive G_{HP} and G_{NH} based on (2.1) and (2.2)
4: **For** G_{HP} and $G^{(i)}{}_{NH}$ **do**
5: Set the output result to 1 and 0 correspondingly
6: Calculate ration coefficient r_i based on (3.5)
7: Derive w_i and $M^{(i)}$ according to (2.6) and (2.7)
8: **End**
9: **End**
10: Train the CNN based on (2.8) (2.9) and (2.10)
11: **Return** The established CNN

Online stage

Input: Sequences to be transmitted X_{in}, decision threshold β

Output: Non-high PAPR sequence output X_{out} and high PAPR sequence output X'_{out}

1: Derive X_{sp} and X_b based on (3.2) and (3.3)
2: Calculate $H^{(i)}{}_b$ according to (3.4)
3: **For** each $\left(c, m, H_b^{(i)}\right)$ **do**
4: **If** $f_c{}^{(i)}$=0
5: Output as X_{out} based on (3.6)
6: **Else**
7: Derive rotation vector factor d_v with (3.8)
8: Output as X'_{out} based on (3.9)
9: **End**
10: **End**
11: **Return** X_{out} and X'_{out}

Table 1. Original data distribution.

Modulation type	Identification class	Number of blocks
QPSK	High PAPR sequences	15
	Non-high PAPR sequences	240
8QAM	High PAPR sequences	134
	Non-high PAPR sequences	3962

Table 2. Data distribution after sampling balance processing.

Identification class	Number of blocks	Weighted value
High PAPR sequences	149	——
Non-high PAPR sequences 1	146	40%
Non-high PAPR sequences 2	303	30%
Non-high PAPR sequences 3	452	20%
Non-high PAPR sequences 4	611	10%

4. Simulation results

In this part,we set the number of subcarriers as 4, and the decision threshold β is set as 0.5, the threshold of high PAPR sequences is set as 7 dB, and the modulation types containing QPSK and 8QAM. After that, the performance of the proposed algorithm is evaluated by three aspects: the performance of the CNN, the computation reduction performance, and the PAPR reduction performance.

4.1. Preprocessing result of the input data

High PAPR sequence is calculated in 4351 blocks (which are independent and different from each other) by using (2.2). The specific distribution is shown in Table 1.

Through (2.4)–(2.7), the unbalanced data is re-sampled, and four different sets of CNN data samples are obtained for training and identifying of high PAPR sequences, which is as shown in Table 2.

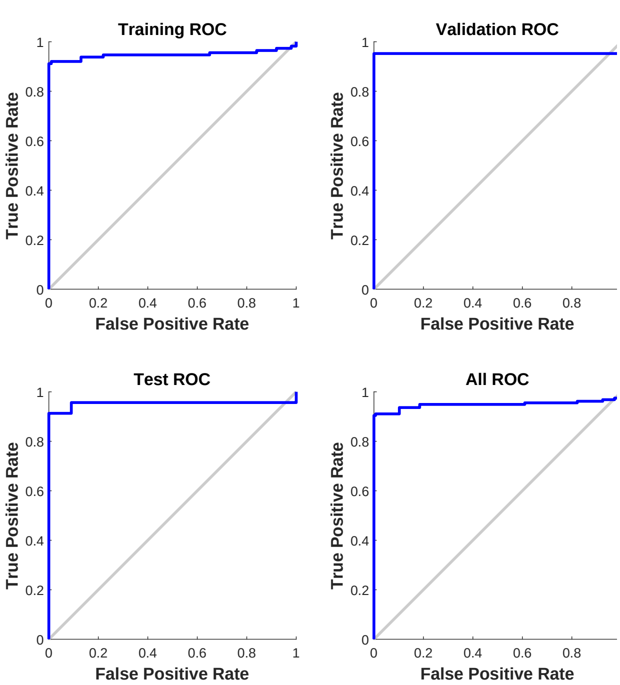
4.2. High PAPR identification performance

Through Table 2, the identification performance of CNNs is derived. As shown in Table 3, the weighted average identification rate of PRD Algorithm for high PAPR sequences is 93.1% at this time, which is derived through weighted performance of each CNN by (2.7).

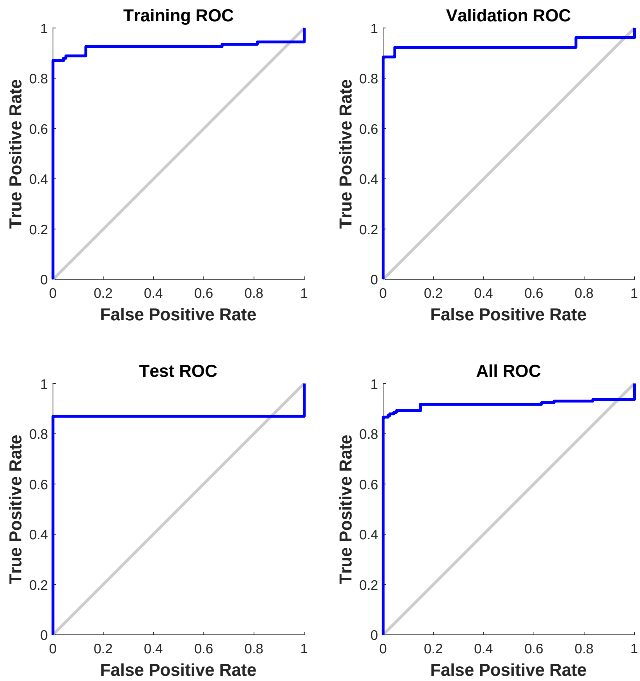
Figure 3 shows the ROC curves of different CNN in the training, verification and test phase in turn.

Table 3. Different CNNs and performances.

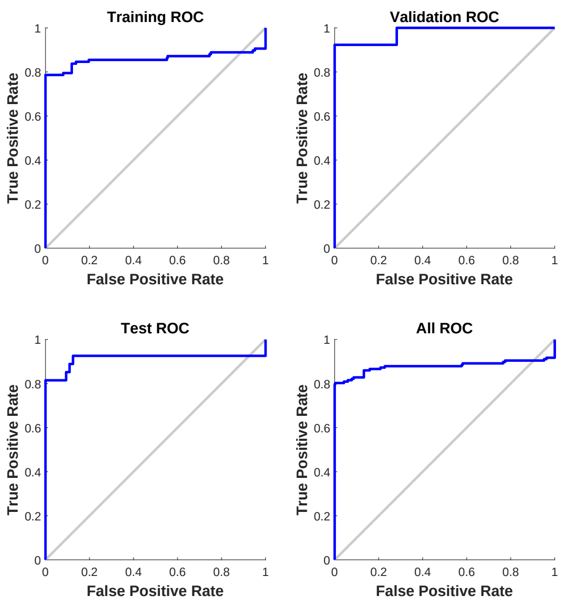
Classification	Identification rate	Weighted value
CNN1	96.1%	40%
CNN2	94.1%	30%
CNN3	93.6%	20%
CNN4	95.2%	10%



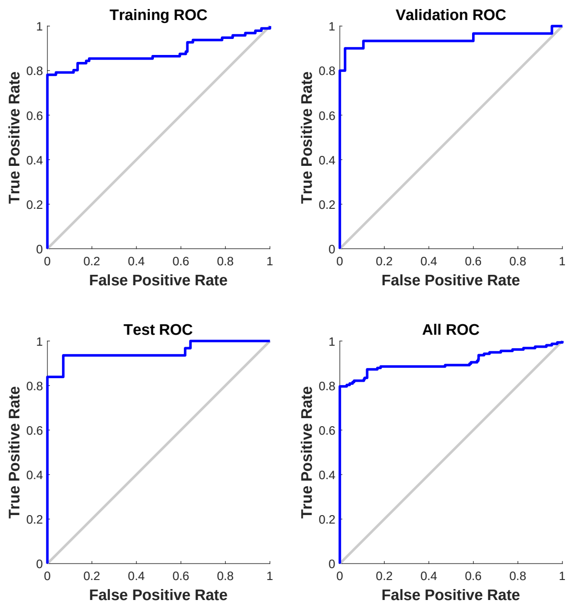
(a) ROC of CNN1



(b) ROC of CNN2



(c) ROC of CNN3



(d) ROC of CNN4

Figure 3. The ROC curve under different CNN.

It can be seen from Figure 3 that when the false alarm rate does not exceed 10%, the probability of successful identification is not less than 90%. Based on (2.7), when the false alarm rate does not exceed 10%, the identification rate for high PAPR of PRD algorithm is 92.3%.

4.3. IFFT computation reduction performance

Under the same parameter settings, the number of IFFT operations with SLM is no less than PTS, so the number of IFFT operations is compared only between the PTS and the PRD Algorithm in this part.

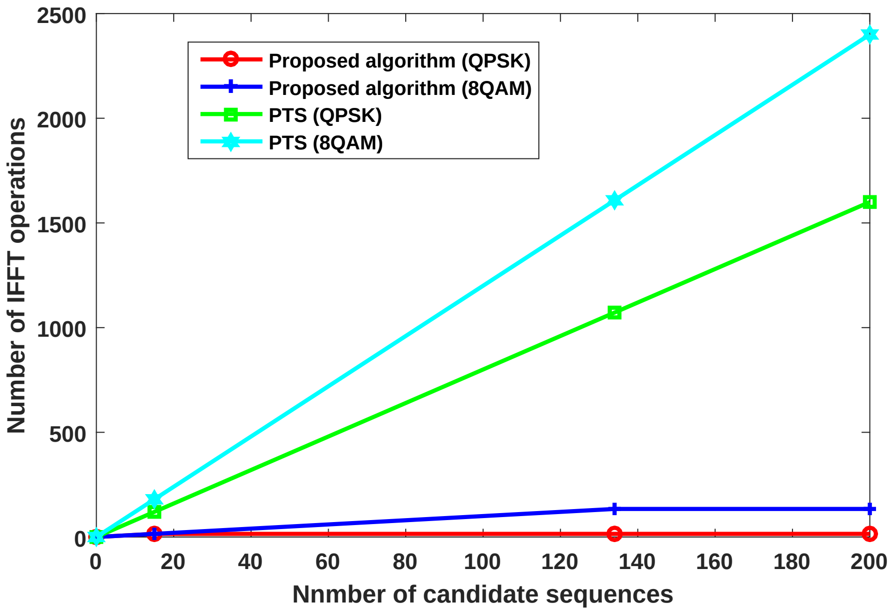


Figure 4. The computation performance.

Figure 4 shows the comparison of the IFFT operation times between the PTS and the proposed PRD algorithm. It can be seen from Figure 4 that when the modulation type is QPSK and the number of candidate sequences is greater than 15, the PRD algorithm only needs 15 IFFT operations to reduce the PAPR of the system at most. The reason is that when the number of candidate sequences is greater than 15, at most 15 high PAPR sequences in the system need to be identified by the established CNN as Table 1 shows. Similarly, under the modulation type of 8QAM, when the number of candidate sequences is greater than 134, the proposed algorithm in this paper requires at most 134 IFFT operations to reduce the PAPR of the system.

4.4. PAPR reduction performance

Figure 5 shows the comparison results of the PAPR reduction performance of different algorithms. It can be seen from Figure 5 that the original OFDM system without PAPR reduction algorithm has a $PAPR_0$ of 9.5 dB when the CCDF is 10^{-3}. The reductions of the SLM, PTS and the PRD algorithms are 4.6 dB, 4.3 dB and 3.6 dB respectively. Although the SLM and the PTS are about 1 dB better than the proposed algorithm for reducing the system's PAPR, it can be seen from Figure 4 that in the case of QPSK, the calculation amount is increased by about 100 times, and in the case of 8QAM,

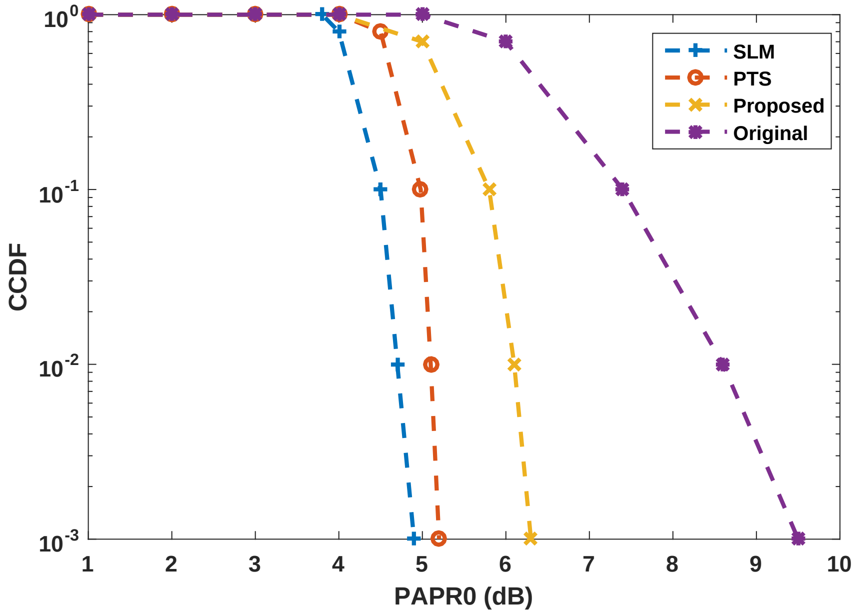


Figure 5. The PAPR reduction performance.

the calculation amount has increased about 18 times. Therefore, comprehensively considering the effectiveness and reliability of the algorithm, the PRD algorithm proposed in this paper can not only reduce the PAPR of the system effectively, but also significantly reduce the complexity of the algorithm.

4.5. Discussion

4.5.1. High speed transmission scenario

According to the work flow of the OFDM system in [13], the data need to be performed serial-to-parallel conversion, IFFT, high PAPR judgement; and when performing the IFFT operations, the traditional method needs to perform IFFT operations for all the input data sequences; while our proposal only needs to input the raw data into the designed CNN, and can get the PAPR identification result in less time than the traditional methods. Therefore, our proposal is more suitable for the high speed transmission scenario, where the processing time for the input data sequences is little.

4.5.2. Sensitivity of input parameters

The proposed CNN-based approach is not sensitive to the input parameters, such as the length of the sequence, the judgement threshold of the High PAPR sequence, modulation types, and the number of the sub-carries, and the reason is that CNN can set the above parameters as the input variables, while the traditional method can not. For example, the CNN method could deal with the situation where the number of the subcarriers and the modulation types are varying, i.e., when the CNN is established, it can be used in the different OFDM systems with different parameters. However, the traditional method does not have such kind of universality and robustness, which needs lots of IFFT operations when the parameters are varying.

4.5.3. Layered CNN-based PAPR reduction

Inspired by the neural network-based coding technology [16], one layered CNN-based PAPR reduction scheme could be our future work. To be detailed, two cooperated CNNs can be designed for the high PAPR sequence reduction, where the CNN in the first layer is responsible for the high PAPR sequence identification, which is achieved in this paper; and the second CNN is responsible for the coding of the identified high PAPR sequence, by which the PAPR can be reduced. Therefore, the layered-CNN method can not only identify the high PAPR sequences with little time, but also reducing the PAPR of the system by automatic coding with CNN.

5. Conclusions

In this paper, to reduce the IFFT operations and save the calculation time under the high speed transmission scenario, we proposed a PAPR (Peak to Average Power Ratio) reduction algorithm, called PRD, based on CNN (Convolutional Neural Network) in OFDM systems. Firstly, CNN is adopted to identify the PAPR signal sequences; and then PTS (Partial transmission sequence) algorithm is applied to reduce the PAPR of identified signals. Simulation results show that the proposed PRD algorithm can identify high PAPR sequences with high accuracy with low computation complexity. In the future, a comprehensive CNN model that contains more types of subcarriers and modulations will be developed.

Acknowledgments

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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