IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received November 26, 2020, accepted December 9, 2020, date of publication December 14, 2020, date of current version December 28, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3044306

Elimination of Noise Distortion for OFDM Systems by Compressed Sensing Based on Distance Metric

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ABSTRACT The clipping method is often applied to reduce the peak to average ratio (PAPR) of orthogonal frequency division multiplexing (OFDM). However, this method will cause in-band distortion, which increases the bit error rate (BER) at the receiver. Clipping distortion recovery techniques can be used to alleviate the problem. This paper proposes a clipping noise recovery scheme based on distance metric (dmCNR). The proposed method estimates the clipping position in the frequency domain, and applies it to the reconstruction algorithm of compressed sensing (CS), which greatly reduces the system complexity. Meanwhile, the method selects the reliable sub-carrier data iteratively to improve the accuracy of clipping distortion recovery. Simulation results verify that the proposed method exhibits good BER performance.

INDEX TERMS Clipping noise, orthogonal frequency division multiplexing (OFDM), distance metric.

I. INTRODUCTION

Orthogonal frequency division multiplexing (OFDM) is a deeply studied and widely used technology. Over the years, due to its strong anti-inter symbol interference, anti-multipath fading and high spectral efficiency, OFDM has been applied in digital video broadcasting (DVB), wireless LAN (WLAN) and digital audio broadcasting [1]–[3]. However, OFDM also exists many problems of its application, one of which is the high PAPR, which limits effective utilization of transmitting power. Aiming at the high PAPR problem, many effective mitigation methods have been proposed [4]–[10]. These methods are roughly divided into three categories: probability technology, coding technology and signal predistortion technology. Among these technologies, clipping is a direct and effective method, it limits the signal's amplitude to a predetermined range [11], [12]. However, clipping will result clipping noise, which affects the bit error rate(BER) at the receiver [13].

Some methods have been proposed to mitigate the harmful effects of clipping distortion [14]–[17]. In [14], a decision-assisted reconstruction technique was proposed, it reduces the impact of clipping noise by reconstructing the unclipping signal in the time domain. In [16], an iterative receiving method is proposed, which estimates and eliminates the clipping noise at the receiver.

In recent years, compressed sensing (CS) is a hot research frontier, which attracts attention on many application fields [18]. Due to the sparsity of clipping noise in the time domain, this theory can be used to reconstruct clipping noise at the receiver [19]–[24], [28]–[32]. In earlier studies, scholars use pilot or reserved subcarriers to recover the clipping noise [21], [23], but this would cause a waste of spectrum resources. Considering this point, some scholars have proposed to selectively use data subcarriers, which can not only improve spectrum utilization, but also reduce channel noise pollution[20]. In [24], a clipping noise recovery method based on auxiliary signal is proposed, the sparse information is hidden in the auxiliary signal and used for the reconstruction process. In [28], an iterative CS algorithm, which uses the observations of data tones and pilot tones, is proposed to reduce the influence of clipping noise. In [29], scholars have proposed a method in which a hybrid approach using clipping and companding is used as the PAPR suppression method, and the nonlinear distortion introduced by the clipping is recovered by CS method at the receiver. In [30], a semianalytic scheme based on CS is proposed to reconstruct the iterative clipping noise, which solves the problem

The associate editor coordinating the review of this manuscript and approving it for publication was Yue Zhang.

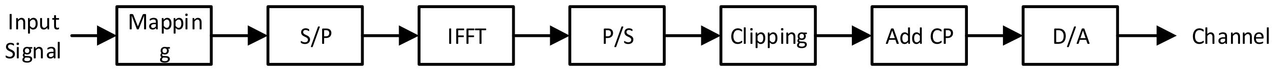

FIGURE 1. **The transmitter block diagram of the OFDM systems.**

that iterative clipping noise violates the sparsity. In [31], scholars have proposed a iterative shrinkage/thresholding algorithm that can select efficient observations by mitigating the effects of channel noise. In [32], pilot signals with phase rotation factor are introduced to modify the OFDM signal at the transmitter to ensure the clipping noise is sparse enough.

In the above literatures, the orthogonal matching pursuit(OMP) algorithm is often used as a reconstruction algorithm to recover clipping noise due to its simple and effective advantages. However, scholars have not considered the optimization of OMP algorithm to reduce its complexity of the reconstruction process. In this paper, we propose a clipping noise recovery algorithm based on distance vector. The main content is as follows:1) A distance criterion is proposed to select the clipping positions with high probability. Based on the location information, we improve the OMP algorithm, which reduces the complexity of clipping distortion reconstruction. 2) At the receiver, an iterative recovery method is proposed. This method continuously updates the decision value of the received signal, which can obtain the observation data with less channel noise pollution, thus get a more accurate clipping noise recovery value.

The rest of this paper is organized as follows: In section II, we introduce the system model. In section III, a clipping noise recovery scheme based on distance vector is proposed. In section IV, we demonstrate the simulation results. Finally, section V draws the conclusion.

II. THE OFDM SYSTEM MODEL

A. OFDM SYSTEM TRANSMITTER

At the transmitter of the OFDM system, as shown in Figure 1, after forward mapping and modulating, the input signal is converted to the OFDM frequency domain signal $\boldsymbol{X}$, then passing $\boldsymbol{X}$ through the fast inverse Fourier Transform (IFFT) module, we obtain the time domain signal $\boldsymbol{x}$:

$$x_{\mathrm{n}} = \frac{1}{N}\sum_{k=0}^{N-1} X_k \exp(\frac{j2\pi kn}{N}), \quad 0 \le n \le N-1. \tag{1}$$

where N is the number of subcarriers, $\boldsymbol{X} = [X_0, X_1, X_2, \ldots, X_{N-1}]$, and $X_k (0 \le \mathrm{k} \le N-1)$ represents the complex symbol on the kth subcarrier.

Then, the ratio of the maximum power to the average power of time domain signal $\boldsymbol{x}$ is defined as the PAPR of OFDM system.

$$PAPR = 10\log\frac{\max[|x_n|^2]}{E[||x_n|^2|]}. \tag{2}$$

where E $\{\cdot\}$ denotes the expectation operation.

The complementary cumulative distribution function (CCDF) is often used to describe the PAPR distribution of OFDM signal, which is defined as the probability that the PAPR of an OFDM signal exceeds a given threshold $PAPR_0$.

$$CCDF = P_r(PAPR \ge PAPR_0). \tag{3}$$

we perform a clipping operation on $\boldsymbol{x}$, which is to limit the signal amplitude below the characteristic threshold. The clipped signal is modeled as follows:

$$\bar{x}_n = \begin{cases} x_n & |x_n| \le A \\ Ae^{j\phi(x_n)}, & |x_n| > A \end{cases}. \tag{4}$$

where A is the given threshold, which is related to the clipping ratio (CR). CR is defined as follows:

$$\mathrm{CR} = 20\log\frac{A}{E[|x_n|]}dB. \tag{5}$$

CR represents the degree of clipping.

The clipped signal $\bar{x}_n$ can be modeled as the sum of the original OFDM signal x_n and the clipping distortion c_n, The frequency domain and the time domain representation are as follows:

$$\bar{x}_n = x_n + c_n, \quad 0 \le n < N. \tag{6}$$

$$\overline{X}_k = X_k + C_k, \quad 0 \le k < N. \tag{7}$$

where $\bar{X}$ is the frequency domain clipping signal and C represents the frequency domain clipping noise. Then, add a cyclic prefix (CP) to the clipped signal, and send it to the channel after D/A conversion.

B. COMPRESSED SENSING OVERVIEW

Compressive sensing (CS) is a newly introduced research field in 2006. It can recover high dimensional signals from highly incomplete linear measurements through effective algorithms, as long as the high-dimensional signals can be sparsely represented with appropriate bases.

Assume the sparse signal $\mathbf{x}$ is a N-dimensional signal and the sparsity is k (it only contains k non-zero values, K≪N), then it can be reduced to M dimensions by a sensing matrix $\boldsymbol{\Phi}$.

$$\mathbf{y} = \Phi\mathbf{x}. \tag{8}$$

where the sensing matrix $\boldsymbol{\Phi} \in R^{M\times N}$, the measurement vector $\mathbf{y} \in R^M, M < N$

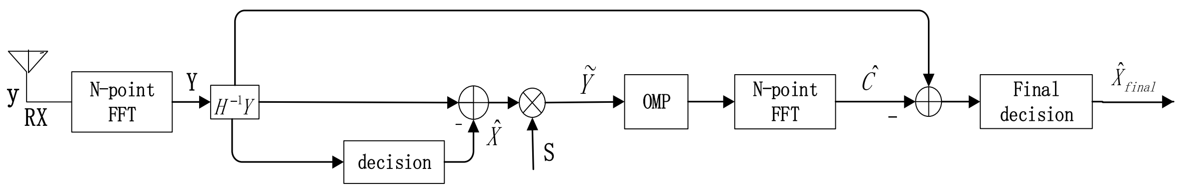

FIGURE 2. The CS-Based OFDM System Receiver block diagram.

If **x** is a non-sparse signal, but can be represented sparsely on a sparse basis, which is expressed as follows:

$$\mathbf{x} = \mathbf{\Psi s}. \tag{9}$$

where $\mathbf{\Psi} \in R^N$, the vector **s** is k-sparse. Substitute (9) into (8), we have

$$\mathbf{y} = \mathbf{\Phi \Psi s} = \boldsymbol{A}\mathbf{s}. \tag{10}$$

where $\boldsymbol{A} = \mathbf{\Phi\Psi}$.

To resolve the equation, scholars propose many recovery algorithms, such as the ℓ_1-norm minimization.

$$\min_{s} ||\boldsymbol{s}||_1 \text{ subject to } \boldsymbol{y} = \boldsymbol{A}\boldsymbol{s}. \tag{11}$$

III. PROPOSED CLIPPING NOISE RECOVERY SCHEME BASED ON DISTANCE METRIC

A. THE OFDM SYSTEM RECEIVER BASED ON CS

In Fig. 2, the OFDM frequency domain received signal is obtained after fast Fourier transform(FFT) process. Combined formula (7), we express the received signal as:

$$\boldsymbol{Y} = \boldsymbol{H}\overline{\boldsymbol{X}} + \boldsymbol{Z} = \boldsymbol{H}(\boldsymbol{X} + \boldsymbol{C}) + \boldsymbol{Z}. \tag{12}$$

where $\boldsymbol{H}$ and $\boldsymbol{Z}$ denote channel response and the additive White Gaussian noise, respectively.

Assuming that the channel response is known and the receiver does not need channel estimation, the equalized signal is expressed as:

$$\boldsymbol{H}^{-1}\boldsymbol{Y} = \boldsymbol{X} + \boldsymbol{C} + \boldsymbol{H}^{-1}\mathbf{Z} = \overline{\boldsymbol{X}} + \boldsymbol{H}^{-1}\mathbf{Z}. \tag{13}$$

We estimate the equalized signal by maximum likelihood estimator, and the initial decision value of $\hat{\boldsymbol{X}}$ is expressed as:

$$\widehat{\boldsymbol{X}} = argmin|\boldsymbol{H}^{-1}\boldsymbol{Y} - s|, s \in \chi. \tag{14}$$

where χ is the preset constellation points set.

Subtract initial decision value $\hat{\boldsymbol{X}}$ from the equalized signal, we obtain the clipping distortion $\boldsymbol{C}$ with observed noise $\boldsymbol{\theta}$:

$$\boldsymbol{H}^{-1}\boldsymbol{Y} - \widehat{\boldsymbol{X}} = \boldsymbol{C} + (\boldsymbol{X} - \widehat{\boldsymbol{X}}) + \boldsymbol{H}^{-1}\boldsymbol{Z} = \boldsymbol{C} + \boldsymbol{\theta}. \tag{15}$$

where the observation noise $\boldsymbol{\theta}$ contains AWGN and decision error.

To reduce the harmful effect of $\boldsymbol{\theta}$, reliable subcarrier data with small observation noise $\boldsymbol{\theta}$ should be selected as the observation vector. This process can be achieved through the following criterion[20]:

$$\boldsymbol{K} = \{k||\widehat{\theta}_k|^2 < E\{|C_k|^2\}\}, 0 \le k < N. \tag{16}$$

where $\boldsymbol{K}$ is the selected subcarrier index set with small observation noise $\boldsymbol{\theta}$.

According to the set $\boldsymbol{K}$, we select the corresponding rows of the identity matrix $\boldsymbol{IM}_N$ to generate the selection matrix $\boldsymbol{S}$. Assuming that the size of $\boldsymbol{K}$ is M, then $\boldsymbol{S} \in R^{\mathrm{MxN}}$.

Based on the formula(15), using the selection matrix $\boldsymbol{S}$, we obtain the reliable observation data $\tilde{\mathbf{Y}}$:

$$\begin{aligned} \widetilde{\boldsymbol{Y}} &= \boldsymbol{S}(\boldsymbol{H}^{-1}\boldsymbol{Y} - \widehat{\boldsymbol{X}}) \\ &= \boldsymbol{S}(\boldsymbol{C} + \boldsymbol{\theta}) \\ &= \boldsymbol{SFc} + \boldsymbol{S\theta} \\ &= \mathbf{\Phi}\boldsymbol{c} + \boldsymbol{\eta}. \end{aligned} \tag{17}$$

where $\boldsymbol{C} = \boldsymbol{Fc}, \boldsymbol{F} \in R^N$ is the Fourier transform matrix, $\boldsymbol{C}$ and $\boldsymbol{c}$ are the frequency domain clipping distortion and the time domain clipping distortion, respectively. Then $\mathbf{\Phi} \in R^{\mathrm{MxN}}$ is the sensing matrix, which has a good restricted isometry property (RIP)[26], and $\boldsymbol{\eta}$ is noise. Since the time domain clipping distortion $\boldsymbol{c}$ is sparse, according to the description of CS in section II-B, the CS reconstruction algorithm can be used to recover it to $\hat{\mathbf{c}}$.

If the formula (15) is directly used as $\tilde{\mathbf{Y}}$ to recover the clipping noise, some data heavily polluted by channel noise in (15) will affect the accuracy of reconstruction. In (17), since $\boldsymbol{K}$ is the subcarrier index set with small observation noise $\boldsymbol{\theta}$, the selection matrix $\boldsymbol{S}$ composed of $\boldsymbol{K}$ and $\boldsymbol{IM}_N$ can select reliable subcarrier data from overall data $(\boldsymbol{C}+\boldsymbol{\theta})$ as the observation vector $\tilde{\boldsymbol{Y}}$.

Finally, the recovered clipping noise $\hat{\boldsymbol{c}}$ is transformed into frequency domain $\hat{\boldsymbol{C}}$. Subtracting $\hat{\boldsymbol{C}}$ from the equalized signal $\boldsymbol{H}^{-1}\mathbf{Y}$, we can make a more accurate decision by the maximum likelihood estimator. The more accurate decision value is given by

$$\widehat{\boldsymbol{X}}_{final} = argmin|\boldsymbol{H}^{-1}\boldsymbol{Y} - \widehat{\boldsymbol{C}} - s|, s \in \chi. \tag{18}$$

In some cases, such as severe channel noise pollution, the criterion of (16) cannot obtain enough reliable observation data, which will lead to poor reconstruction performance of CS. To prevent this, we set the size of $\mathcal{K}$ to be M, M$= \lfloor \rho \mathrm{N} \rfloor$. According to[27], $\rho = 0.6 \sim 0.8$ can ensure enough observation data for reconstruction, so in the following simulation, we set $\rho = 0.65$. In the following, we will elaborate the proposed clipping distortion recovery scheme based on the above receiving structure.

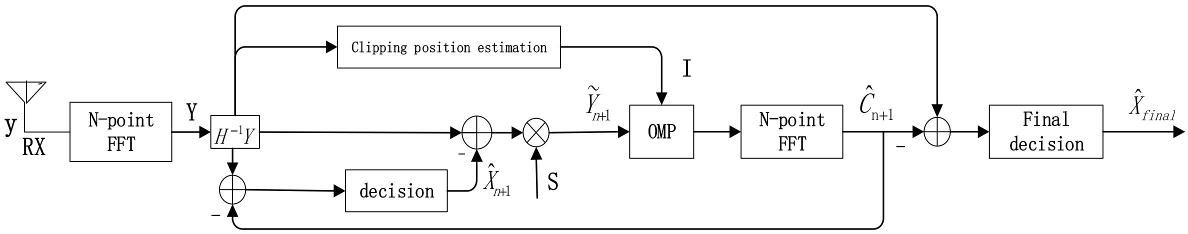

FIGURE 3. Receiver of proposed scheme.

B. IMPROVED OMP SCHEME BASED ON THE DISTANCE VECTOR

At the transmitter, the amplitude of the clipping position is clipped to the threshold value, while the amplitude of the unclipped position remains unchanged. Therefore, in the ideal situation, the distance between signal point at the clipping position and the threshold is zero, while the distance between signal point at other positions and the threshold is greater than zero. Based on the principle, we propose a decision criterion in (19), which can obtain a rough estimate of the clipping position from the equalized signal at the receiver.

$$\boldsymbol{I} = \{\mathrm{i} \mid \left| |\mathrm{H}_i^{-1}\mathrm{Y}_i| - \mathrm{A} \right| < \alpha \mathrm{A}\}, \quad 0 \leq i < N. \qquad (19)$$

where i is the subcarrier index, A is the clipping threshold. α is a configurable coefficient according to different conditions, a large number of simulation experiments have shown that the system has good BER performance when the value of α is set to 0.65. $\boldsymbol{H}^{-1}\mathbf{Y}$ represents the equalization signal, and $\boldsymbol{I}$ is the set of clipping positions with high probability.

It can be known from (13), affected by the channel noise $\boldsymbol{H}^{-1}\boldsymbol{Z}$, the distance between the signal point at the clipping position and the threshold is not zero, but the distance value will be smaller than that at other positions. According to this inequality in (19), we can eliminate some unclipped positions and get a rough estimation $\boldsymbol{I}$ of clipped positions.

At the receiver, we use the classical oarthogonal matching pursuit algorithm (OMP) to reconstruct the clipping noise where the sparsity K is calculated at the transmitter and transmitted to the receiver as the input value of the algorithm. The specific reconstruction process is as follows:

1) Initialization: $\boldsymbol{r}_0 = \boldsymbol{y}, \boldsymbol{B}_0 = \phi, \boldsymbol{\Lambda}_0 = \phi, t = 1$.
   where t is the number of iterations, $\boldsymbol{r}_0$ is the initial residual, $\boldsymbol{B}_0$ and $\boldsymbol{\Lambda}_0$ are the column set of sensing matrix $\boldsymbol{A}$ corresponding to clipping positions and clipping position set, respectively.
2) Calculate the inner product and select the index λ_t corresponding to the maximum value: $\lambda_t = \arg\max_j | < \boldsymbol{r}_{t-1}, \boldsymbol{a}_j > |$.
   where $\boldsymbol{a}_j$ is the j-th column of sensing matrix $\boldsymbol{A}$.
3) Update vector $\boldsymbol{\Lambda}_t$ and $\boldsymbol{B}_t$: $\boldsymbol{\Lambda}_t = \boldsymbol{\Lambda}_{t-1} \cup \{\lambda_t, \boldsymbol{B}_t = \boldsymbol{B}_{t-1} \cup \boldsymbol{a}_{\lambda_t}$.
4) Update the residual: $\boldsymbol{r}_t = \boldsymbol{y} - \boldsymbol{B}_t\hat{\boldsymbol{\theta}}_t$.
5) Return to step 2($t = t + 1$) until the iteration terminates($t >$ K).

To reduce the computational complexity of the OMP algorithm, as shown in Figure 3 and algorithm 1, we apply the set $\boldsymbol{I}$ obtained in (19) to the inner product operations of OMP algorithm. As shown in line 2 of algorithm 1, in each iteration of the OMP algorithm, the OMP algorithm only performs inner product with the columns of the sensing matrix $\boldsymbol{A}$ corresponding to the set $\boldsymbol{I}$. Assuming that the size of set $\boldsymbol{I}$ is P, this change will reduce the number of inner product operations from N to P. In other words, the search range for clipping location is reduced from N subcarrier indexes to P, thus reducing the complexity of OMP algorithm ($P \leq N$).

TABLE 1. DMOMP algorithm.

Algorithm 1 dm-omp: The Orthogonal Matching Pursuit algorithm based on distance measurement

Input: (1) Clipping position estimation set $\boldsymbol{I}$; (2) M-dimensional observation vector $\boldsymbol{y}$; (3) M × N dimension sensing matrix $\boldsymbol{A}$;(4) Signal sparsity K

1: **Initialization:** Clipping distortion $\boldsymbol{r}_0 = \boldsymbol{y}$; $\boldsymbol{B}_0 = \phi$; $\boldsymbol{\Lambda}_0 = \phi$;$t = 1$.

Iterations:

2: Compute the index $\lambda_t = arg \max_{j \in \boldsymbol{I}} | < \boldsymbol{r}_{t-1}, \boldsymbol{a}_j > |$,where $\boldsymbol{a}_j$ is the j-th column of vector $\boldsymbol{A}$.

3: $\boldsymbol{\Lambda}_t = \boldsymbol{\Lambda}_{t-1} \cup \{\lambda_t\}, \boldsymbol{B}_t = \boldsymbol{B}_{t-1} \cup \boldsymbol{a}_{\lambda_t}$.

4: Calculate the Least-squares Minimization $\hat{\boldsymbol{\theta}}_t = \arg\min_{\boldsymbol{\theta}_t} ||\boldsymbol{y} - \boldsymbol{B}_t\boldsymbol{\theta}_t||$.

5: Update the residual $\boldsymbol{r}_t = \boldsymbol{y} - \boldsymbol{B}_t\hat{\boldsymbol{\theta}}_t$.

6: $t = t + 1$.

7: **until** $t >$ K.

8: Reconstructing the sparse signal $\hat{\boldsymbol{\theta}}$,which has a value of $\hat{\boldsymbol{\theta}}_t$ on the index set $\boldsymbol{\Lambda}_t$ and zero on the remaining positions.

Output: The sparse signal estimation $\hat{\boldsymbol{\theta}}$.

C. ITERATIVE RECOVERY OF CLIPPING DISTORTION BASED ON RELIABLE OBSERVED DATA

In previous studies, we conclude that reliable observation data can improve the accuracy of clipping noise recovery. At the receiver, we select reliable observation data by constructing an appropriate selection matrix $\boldsymbol{S}$. The selection matrix $\boldsymbol{S}$ is generated according to the value of the observation noise $\boldsymbol{\theta}$, and the decision error $(\boldsymbol{X} - \hat{\boldsymbol{X}})$ can affect the value of $\boldsymbol{\theta}$. Thus the decision error is related to the clipping distortion recovery. According to (20), the smaller the decision error is, the smaller the observation noise will be, meanwhile, the selection matrix will also change accordingly. Finally, the selected observation data will be more reliable, and the clipping distortion recovery will be more accurate.

$$\begin{aligned}\widetilde{\boldsymbol{Y}} &= \boldsymbol{S}(\boldsymbol{H}^{-1}\boldsymbol{Y} - \widehat{\boldsymbol{X}}) \\ &= \boldsymbol{S}(\boldsymbol{C} + (\boldsymbol{X} - \widehat{\boldsymbol{X}}) + \boldsymbol{H}^{-1}\boldsymbol{Z}) \\ &= \boldsymbol{S}(\boldsymbol{C} + \theta) \\ &= \boldsymbol{\Phi}\mathrm{c} + \boldsymbol{\eta}. \end{aligned} \quad (20)$$

Therefore, based on algorithm 1, we propose an iterative receiver. The block diagram is shown in Figure 3. After we obtain the clipping distortion $\hat{\boldsymbol{C}}_n$, we return $\hat{\boldsymbol{C}}_n$ and subtract it from the equalized signal. Then we judge the result again and get a more accurate decision value $\hat{\boldsymbol{X}}_{n+1}$ of $\boldsymbol{X}$. The formula is as follows:

$$\begin{aligned}\widehat{\boldsymbol{X}}_{n+1} &= argmin|\boldsymbol{H}^{-1}\boldsymbol{Y} - \widehat{\boldsymbol{C}}_n - s| \\ &= argmin|\boldsymbol{X} + (\boldsymbol{C} - \widehat{\boldsymbol{C}}_n) - s|, s \in \chi. \end{aligned} \quad (21)$$

The more accurate decision value $\hat{\boldsymbol{X}}_{n+1}$ can be used to acquire smaller decision error $(\hat{\boldsymbol{X}} - \hat{\boldsymbol{X}}_{n+1})$ and smaller observation noise $\boldsymbol{\theta}_{n+1}$. Then according to (16), selection matrix $\boldsymbol{S}_{n+1}$ is updated and used for generating more reliable observations $\tilde{\boldsymbol{Y}}_{n+1}$.

Next, based on $\tilde{\boldsymbol{Y}}_{n+1}$, we get a more accurate $\hat{\boldsymbol{C}}_{n+1}$ by algorithm 1. Iteratively repeats until the final decision value $\hat{\boldsymbol{X}}_{final}$ is obtained.

Assuming that $\hat{\boldsymbol{C}}_0$ is a zero matrix, the first decision value of $\boldsymbol{X}$ is as follows:

$$\begin{aligned}\widehat{\boldsymbol{X}}_0 &= argmin|\boldsymbol{H}^{-1}\boldsymbol{Y} - s| \\ &= argmin|\boldsymbol{X} + \boldsymbol{C} - s|, s \in c. \end{aligned} \quad (22)$$

Combining algorithm 1,2 and the block diagram 3, the steps of the proposed method are described as follows:

1) Get the clipping position estimation $\boldsymbol{I}$ and the initial decision value $\hat{\boldsymbol{X}}_0$ from equalized signal $\boldsymbol{H}^{-1}\boldsymbol{Y}$ according to (19) and (22);
2) Calculate the selection matrix $\boldsymbol{S}$ according to (16);
3) Calculate observation vector $\tilde{\boldsymbol{Y}}$ according to (20);
4) Reconstruct the clipping noise $\hat{\boldsymbol{C}}_{n+1}$ by the algorithm 1;
5) Update the decision value $\hat{\boldsymbol{X}}_{n+1}$, the selection matrix $\mathbf{S}_{n+1}$ and the observation vector $\tilde{\boldsymbol{Y}}_{n+1}$ sequentially according to (21),(16),(20);
6) Return to step 4 until the iteration terminates (algorithm 2), and output the final decision value $\hat{\boldsymbol{X}}_{\mathrm{final}}$.

D. COMPLEXITY ANALYSIS PROPOSED SCHEME

The computational complexity of the OMP algorithm is O(KMN)[25], which mainly consists of two parts: the inner product operation and the least square operation. The computational complexity of the proposed scheme includes the following parts: 1) Firstiy, the complexity of calculating the clipping position estimation set $\boldsymbol{I}$ is O(N). 2) Then, the complexity of reliable observational data acquisition is O(N+log_2 (N) +MN). 3) Next, by the rough estimation of the clipping position based on the distance metric, the improved OMP algorithm can reduce the complexity to O(KMP)(P $\leq N$). Finally, while our proposed algorithm uses iterative reception at the receiver, the simulation results show that only 2-3 iterations, the proposed algorithm can obtain a stable and good BER performance, so the overall complexity of the iterative receiver is O(KMP + MN).

TABLE 2. Iterative clipping distortion recovery.

Algorithm 2 Iterative Recovery of Clipping Noise
Input: (1) Received signal $\boldsymbol{Y}$; (2) Chanel response $\boldsymbol{H}$; (3) Iterative number $N_{iter.}$
1: **Initialization:** Clipping distortion $\widehat{\boldsymbol{C}}_0 = \phi$; $t = 0$.
Iterations:
2: **repeat**
3: Estimate $(\boldsymbol{H}^{-1}\boldsymbol{Y} - \widehat{\boldsymbol{C}}_t)$ to get $\widehat{\boldsymbol{X}}_t$.
4: Update $\boldsymbol{S}_t$, $\widetilde{\boldsymbol{Y}}_t$ and recover the clipping distortion $\widehat{\boldsymbol{c}}_{t+1}$ by the dm-OMP algorithm.
5: The frequency domain clipping distortion $\widehat{\boldsymbol{C}}_{t+1}$ is obtained by FFT.
6: $t = t + 1$.
7: **until** $t < N_{iter.}$
8: Make the final ML estimate of $(\boldsymbol{H}^{-1}\boldsymbol{Y} - \widehat{\boldsymbol{C}}_t)$ to get the output $\widehat{\boldsymbol{X}}$.
Output: Frequency domain signal $\widehat{\boldsymbol{X}}$.

For comparison, we analyze the complexity of another three clipping noise recovery schemes by OMP algorithm. The computational complexity of the roCNC scheme in [20] is O ((K + 1)MN), which includes the acquisition of reliable observation data and traditional OMP algorithm. The computational complexity of the AICS scheme in [29] is O (KMN + 3N), which includes the decompanding operation and OMP algorithm. Besides, the scheme also needs corresponding companding operation, since it uses a hybrid scheme combining companding transformation and clipping at the transmitter. The computational complexity of the saCDR scheme in [24] is O (KM + MN), which includes the acquisition of reliable observation data and improved OMP algorithm based on auxiliary signal. Besides, the scheme also needs generate the corresponding auxiliary signal at the transmitter.

The BER performance of these schemes will be simulated and compared in the next section.

IV. SIMULATION RESULTS

To evaluate the performance of the proposed algorithm, a lot of simulations have been done in this section. In the simulation, we use 256 sub-carriers, the constellation modulation method is 16PSK. For comparison, another four clipping noise recovery schemes by OMP algorithm are added as control groups.

Figure 4 shows the PAPR reduction performance of the proposed scheme. In the figure, we set CR to 4dB, the PAPR in the case of unclipping and clipping without recovery is added for comparison. As shown in the figure, the PAPR performance of the saCDR scheme in [24] is the worst, because at the transmitter, this scheme needs to generate an auxiliary signal for carrying clipping information, which will increase the average power of OFDM signal. The roCNC scheme in [29] uses a hybrid scheme combining companding transformation and clipping at the transmitter, so the PAPR performance of the scheme is the best. The remaining three clipping noise recovery schemes, including OMP, roCNC[20] and the proposed scheme dm-CNR, have the same PAPR performance as the traditional clipping scheme, since they only processes clipping operation on the OFDM signal at the receiver.

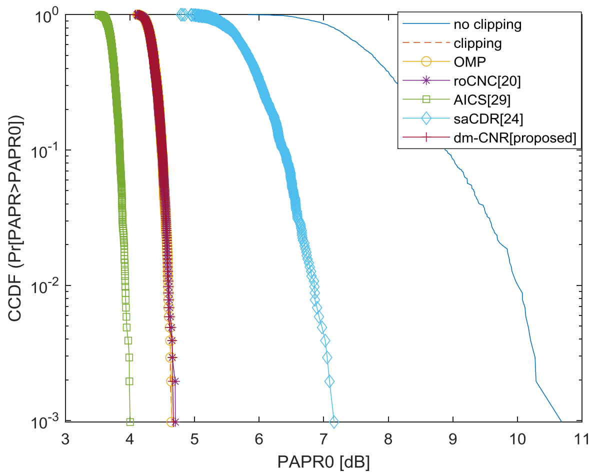

FIGURE 4. The CCDF performance of the proposed scheme.

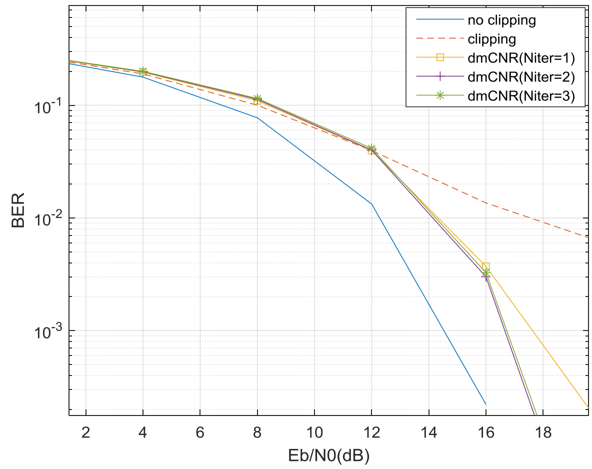

FIGURE 5. The BER performance with different iteration number.

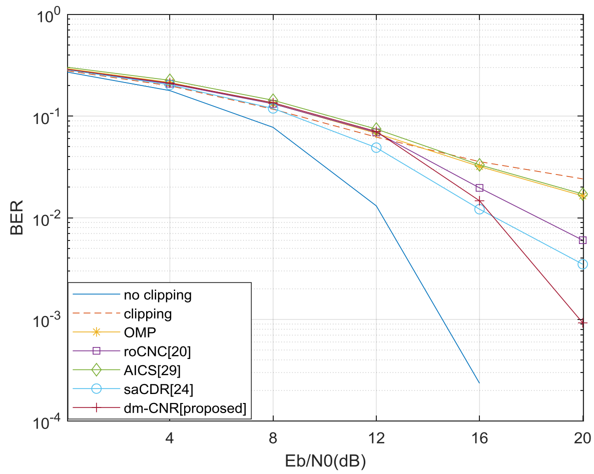

FIGURE 6. The BER performance comparison with CR =3dB.

Figure 5 shows the effect of the iteration number Niter on the BER performance under the AWGN channel. CR is set to 4dB. In figure 5, we find that the BER performance gradually improves when the iteration number increases, especially when the SNR is greater than 16dB. When the Niter value is 2 or 3, the BER performance tends to be stable. For convenience, in the following simulations, we all set the iteration number Niter to 3.

Figure 6 and 7 show the BER performance of proposed scheme under the AWGN channel. In figure 6, CR is set to 3dB.

Comparing the BER performance of different algorithms, we find that the BER performance of the proposed scheme is better than the other algorithms, especially when the SNR is greater than 16dB. This is because the improved OMP algorithm in the proposed scheme dm-CNR can select observation data with less noise pollution for reconstruction. In addition, the proposed scheme uses iterative reception to continuously reduce the observation noise and further improves the reliability of the observation data, which improves the accuracy of the reconstruction. Compared with

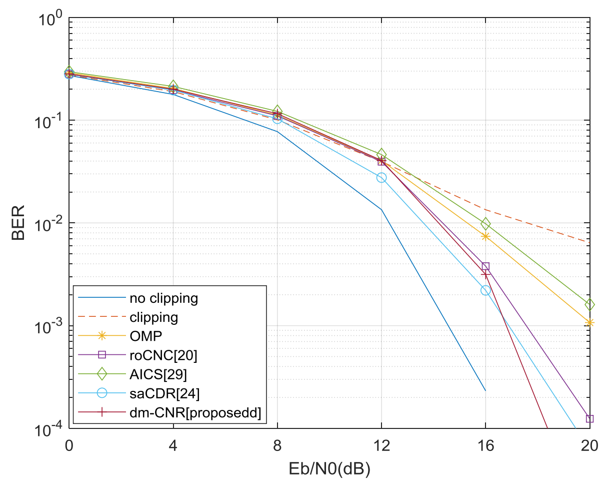

FIGURE 7. The BER performance comparison with CR =4dB.

the traditional OMP scheme, the BER performance of AICS scheme is slightly worse, which is due to more nonlinear distortion caused by the hybrid scheme of companding and clipping at the transmitter. Although the clipping noise is reconstructed by OMP algorithm, the companding noise generated by companding transformation still exists. No matter in low SNR region or high SNR region, scheme saCDR in [24] can keep good BER performance because it uses an auxiliary signal to transmit clipping information, and then uses OMP algorithm to reconstruct clipping noise based on these information. Compared with the other four schemes, which directly use OMP algorithm to calculate clipping information and reconstruct clipping distortion, the improved OMP algorithm in saCDR scheme is less affected by channel noise.

In Figure 7, CR is set to 4dB. The BER performance of all schemes with CR is 4dB is better than that of CR is 3dB, this is because as the CR increases, the sparsity of the clipping noise becomes better, thus the clipping noise recovery based on CS is more accurate. As shown in the figure, the proposed scheme exhibits BER performance consistent with that shown in Figure 6. Combining Fig. 6 and Fig.7, we conclude that the proposed scheme can perform well under different clipping ratios.

The BER performance of different schemes under the Rayleigh channel is shown in Figure 8, where the simulation parameter settings are consistent with Figure 7. In Figure 8, the proposed method outperforms the saCDR scheme and the roCNC scheme by approximately 2dB when the BER is 10^{-2}. Although the roCNC scheme can also select reliable observation data, the proposed scheme applies the iterative receiving structure based on the reliable observation data, which further improves the reliability of the reconstruction. The auxiliary signal in saCDR scheme mainly reduces the complexity of OMP algorithm, but it is less helpful to improve the reconstruction accuracy in Rayleigh channel. The BER performance of the proposed scheme is far better than that of the AICS scheme and OMP scheme, because these two schemes do not process the received data, which leads to some data seriously polluted by the channel noise used in OMP algorithm, moreover, the companding transform in AICS scheme introduces more nonlinear distortion, which leads to the decline of reconstruction accuracy.

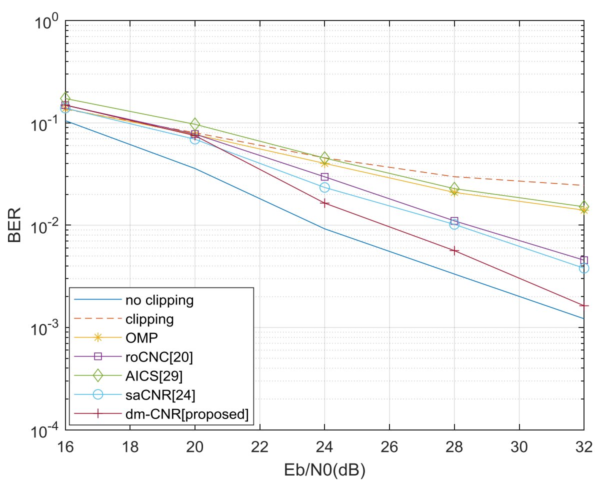

FIGURE 8. The BER performance comparison under Rayleigh channel.

The BER performance of different schemes with error-correcting code adopted is shown in Figure 9, where the simulation parameter settings are consistent with Figure 7. In the figure, we find that the BER performance of all the schemes is better than that without error correcting code adopted in the higher SNR region. The approximate trend of curves in all schemes is similar to that in Figure 7. The BER performance of the proposed scheme is better than the other algorithms, especially when the SNR is greater than 12dB. Combining Fig. 8 and Fig.9, we conclude that the proposed scheme can perform well in different scenarios.

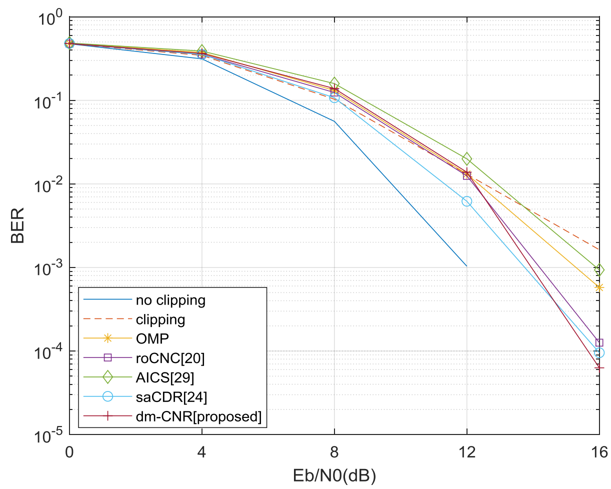

FIGURE 9. The BER performance with error-correcting code adopted.

V. CONCLUSION

In this paper, a clipping noise elimination scheme based on distance metric is proposed. The proposed method selects reliable data in frequency domain to recover the clipping distortion. This method uses a decision criterion to obtain the preliminary estimate of clipping position, which reduces the complexity of the CS reconstruction algorithm. A large number of simulations show that compared with other algorithms, this method can significantly improve the accuracy of clipping distortion recovery and has good adaptability under different channels.

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