

Research Article SCWOMP Recovery Algorithm for 5G MIMO Communication Symbol Detection

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Received 15 December 2022; Revised 9 June 2023; Accepted 29 June 2023; Published 14 July 2023

Academic Editor: Jaafar Gaber

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In order to solve the problem of small capacity and high energy consumption in China's 5G communication technology system, the research proposes that based on the segmented weakly orthogonal matching pursuit (SWOMP) algorithm, it is combined with the compressed sensing matching pursuit algorithm to form a segmented backtracking weak selection positive algorithm and Cross Match Tracking (SCWOMP) algorithm. First, the sparseness of MIMO system technology and its transmission structure is analyzed. Then, the new model is built after comparing with other algorithms, and the problem of overestimating the low recovery probability in the calculation process is improved by the backtracking of the algorithm and the improvement of the angle of the atomic column selection, so as to reduce the number of iterations and improve the performance of the algorithm. The results show that, in the performance comparison of different sampling points under different compressed sensing recovery algorithms, the recovery probability of the SCWOMP algorithm is the best, and when the number of sampling points is 80, although the fixed step size of the SCWOMP algorithm is different, there is recovery. The probability has a maximum value, close to 1. Then, the improved compressed sensing recovery algorithm is simulated and analyzed. When the pruning coefficient is 0.5 and the number of sampling points is 80, the reconstruction rate has a maximum value, and when other algorithms reach the maximum reconstruction rate, the number of sampling points (*M*) is significantly greater than that of the SCWOMP algorithm. An increase in the rate of reduction of the reconstruction probability of the SCWOMP algorithm is significantly lower than that of other algorithms; when sparsity is equal to 70, the reconstruction probability becomes 0, indicating that SCWOMP has a wider reconfigurable range and has a significant performance effect. This shows that the proposed SCWOMP algorithm has the best detection performance for 5G communication symbol detection, which can effectively increase the capacity of the system and better promote technology.

1. Introduction

With the rapid development of modern technology, 5G technology has once again become a research hotspot in the field of communication. With the continuous increase in various communication services, the demand for the wireless transmission rate and symbol detection shows a continuous increase. However, under the condition of very developed science and technology at this stage, the network is an important means to realize human-computer interaction [1, 2]. How to improve the network rate, make the network system capacity and transmission rate more excellent, and reduce unnecessary computation are a few problems to solve [3]. In order to solve the above problems,

this study analyses the sparsity of MIMO systems and proposes a segmented backtracking weakly selective orthogonal matching and tracking algorithm (SCWOMP) in combination with a compression-aware matching and tracking algorithm, which is applied to 5G network systems. In communication, a simulation analysis of sampling points and sparsity is carried out for various Baran algorithms in order to provide people with a good experience [4, 5]. The MIMO technology involved in the research is developing rapidly, and the SCWOMP algorithm is a recovery algorithm with fewer iterations and a better recovery rate, which is suitable for unsupervised learning programs such as communication system networks. The simulation data and models generated during the experiment can produce good data. The two are combined with each other, and the comparison between the original waveform and the recovered waveform is used to verify the superiority of the algorithm performance. This has innovative significance for China's current communication technology and data costs and can promote the development and progress of science and technology.

2. Related Works

With the expansion of the layers and fields involved in 5G technology, new MIMO technology has gradually entered people's field of vision, and more and more scholars have begun to study the combination of the compressive sensing reconstruction algorithm and SWOMP. In order to estimate and grasp the state of all targets, Zhang et al. proposed an adaptive Kalman information filtering algorithm. When the communication network is observed, the sensor network is variable, and the collective can be observed, it can be proved that the system matrix of the target is invariant. The effectiveness of the algorithm is proved in simulation experiments [6]. Qu and Li proposed a distributed algorithm to cope with the accuracy of communication networks in an iterative process. The algorithm can effectively utilize the smoothness of the function and quickly converge to the optimal solution at a certain speed, which means that the algorithm has a linear convergence speed. These two speeds are in line with the convergence speed of CGD. The algorithm includes a gradient estimation scheme that enables a fast and accurate implementation of the average gradient using past historical information [7]. In order to provide strong infrastructure and services, Shen and Chen proposed a load-balancing method (RIAL) using resource intensity awareness. For each different heavy-load physical machine (PM), the algorithm will reasonably allocate resources according to different PM usage intensity and dynamics. The practice can greatly reduce the time and cost. Algorithmically, tuning virtual machines (VMs) to reduce bandwidth costs has superior performance compared to other algorithms [8]. Li and Zhao conducted research on adaptive multiagent systems and found a nonlinear switching multiagent system with regard to the nonstrict feedback form and input saturation. The process is represented by the Gaussian error function and the unsaturated model. The algorithm is used to approximate some unknown encapsulated functions, and the inverse process is used to build a public function. On this basis, an adaptive consensus protocol is also proposed to make the tracking error converge to a minimum under arbitrary switching [9]. Saleem et al. proposed a speech enhancement algorithm capable of supervised sub-single-phase channel speech enhancement for the problem of speech enhancement. The speed-up algorithm is based on a strong deep neural network (DNN) and a weaker Wiener filter as the DNN layer in the process. In the initial stage, the network learns speech features from the input noisy speech signal and extracts clean and noisy signals. The results show that the proposed algorithm is excellent in both speech quality and intelligibility [10].

Wei and Liao studied the design of the transmitted waves of a MIMO radar system using a DAC. In order to solve the optimization problem composed of the constrained fractional quadratic problem, the sparse semidefinite relaxation method is used to transform the problem into monthly reduced convex semidefinite programming (SDP). It is also proposed to utilize a customized interior point algorithm to solve small-scale SDP problems. The desired sequence of bit transmit waveforms is also appropriately synthesized by a Gaussian randomization problem. The results show that the method has good performance [11]. Baek et al. proposed a simple method for applying deep learning neural network algorithms to traditional multiple-input multiple-output (MIMO) communication systems. In the process, the signal detection of the single-tap MIMO channel with the basic DNN structure is used, and the convolutional neural network and the recurrent neural network are proposed for the reason of the multipath fading channel in the system. It is proved by experiments that the proposed two structures can effectively transmit the correct system signal [12]. Zhou et al. investigated the ability of active beamforming to reduce user equipment (UE) positioning errors in MIMO systems. This research is quite challenging, and to address this challenge, a novel sequential localization and beamforming (SLAB) scheme is proposed. In the process, the long-term UE position and the instantaneous channel state are combined, and continuous optimization is carried out according to the obtained estimated value. Simulation experiments show that the proposed scheme outperforms the existing baselines [13]. Mehrabi et al. proposed a decision-directed (DD) channel estimation (CE) algorithm for multiple-input multiple-output (MIMO) systems in the vehicle environment of a high-speed moving vehicle. During the process, the Doppler rate in the vehicle communication system is very variable, requiring a large number of pilots and preambles to intervene. Simulation results show that, compared with other existing algorithms, the proposed DL-based DD-CE algorithm can have a lower propagation error and better grasp of Doppler frequency [14]. Zhong and Chongjun proposed a piecewise OMP (POMP) method for modern 5G application problems. This algorithm can well preserve the piecewise sparse structure of the piecewise signal. Based on the advantages of the OMP algorithm, the POMP algorithm also has the roles of CoSaMP and OMMP in piecewise sparse recovery, which can more accurately approximate the error attenuation and use better sufficient conditions and better recovery success rates. The proposed algorithm performs better repair of segmented sparse signals according to the segmental structure of the communication signal and is more stable and effective than other algorithms [15].

In summary, in the current new intelligent era, the network communication and technology is developing rapidly, how to detect the communication symbols, improve the system capacity and reduce the energy consumption has also attracted extensive attention from researchers. Among them, the MIMO system technology has been known for a long time, but the SCWOMP algorithm is improved by combining compressive sensing reconstruction and MIMO, and the proposed algorithm is improved to build a model and improve performance. It is urgent to provide new directions and ideas for the research of communication technology systems through this research.

3. Improved Algorithm Design of the SWOMP Algorithm in Symbol Detection of the Communication Technology System

3.1. Analysis of the MIMO Technology System and the Compression Sensing Recovery Algorithm. Multiple-input multiple-output (MIMO) system technology communication is a wireless communication system that uses multiple antennas in common between the transmitter and receiver. But based on various considerations, generalized spatial modulation (GSM) is usually regarded as a part of the MIMO system [16, 17]. GSM is a special MIMO system where the transmitting unit is larger than the transmitting unit derived from the spatial modulation multiple-input multiple-output (SM-MIMO) system of a single RF spatial modulation MIMO system. This system retains the basic transmission characteristics of SM-MIMO and is not limited to a single active antenna. Unlike spatial multiplexing, the main difference between spatial modulation systems and spatial multiplexing is that information bit blocks are mapped into two information carrying units: spatial constellation symbols and signal constellation symbols. When sending, only one or a few antennas are activated, which reduces the number of links and provides the possibility of reducing hardware costs for the receiving end, giving it more development advantages. The transmission signal of the GSM system is shown in equation (1). At the same time, if the information of the perfect channel has been obtained, the corresponding system's reception model is expressed in the following equation:

$$\begin{cases} x = [-1+i, 0, 0, -1+i], \\ y = Hx + \sqrt{\frac{N_{\tau}E_x}{\rho n}}. \end{cases}$$
(1)

In equation (1), y represents $N_r \times 1$ the sequence vector. N_{τ} represents the number of input signal antennas in the MIMO system, S represents the set of constellation symbols, x represents $N_r \times 1$ a vector of numbers, where sparsity is N_A , that is, $x \in S^{N_T \times 1}$, H and C both represent matrices, the channel matrix of $H \in C^{N_T \times N_R}$ and $N_T \times N_R$ represent the order of spatial diversity, n represents white Gaussian noise, ρ represents the signal-to-noise ratio, and $E_x = \sum_{i=1}^{N_T} E_i$ $||x_i||_2^2/N_T$ is the average value of the energy contained in the transmitted symbols. This is a 5G communication system built through spatial modulation technology, which is no longer limited to traditional amplitude modulation and phase modulation, but extends the modulation content from the numerical field to 3D spatial characteristics. In a physical sense, it is understood that the serial number of the transmitting antenna is used as one of the mapping relationships for information transmission. This enriches the transmission methods of information, but overall, due to the small number of receiving antennas for users and the large number of antennas for BS, signal detection in the system is essentially a challenging large-scale underdetermined problem. The mode of the transmission signal is sparse. In order to better detect symbols in MIMO systems, the research proposes to combine compression sensing with improved recovery algorithms. Compressed sensing can effectively reduce the sampling process and unify the sparsity and sampling process into a sensing process. In the process, *s* is the length of the discrete signal set as *N* and the element is expressed as x[N]; then, the specific expression is shown in the following equation:

$$s = \sum_{i=1}^{N} x_i \psi_i = \Psi x.$$
 (2)

In equation (2), x represents the sequence vector of the weighting coefficient, s and x have the same effect, but s is expressed in the space-time domain, and x is expressed in the Ψ domain. We reexpress y through integration, as shown in the following equation:

$$y = \Phi s = \Phi \Psi x = \Theta x. \tag{3}$$

In equation (3), $\Theta = \Phi \Psi$ is an $M \times N$ matrix. Compressed sensing Φ is fixed and does not depend on the signal *s*. The model is summarized in Figure 1.

Figure 1 shows that there are three overall important processes: the sparseness of the nonsparse signal, the design of the sensing matrix, and the reconstruction algorithm of the signal. The SCWOMP algorithm is reconstructed and improved by using compressed sensing. If the number of nonzero items is smaller than the dimension of the vector, the vector is called a sparse vector. To examine the measure of sparsity, the *s* norm of the $||s||_0$ vector is used here ℓ_0 , which is defined as the following equation:

$$\|s\|_{0} = \{i : s_{i} \neq 0\}.$$
 (4)

In equation (4), when $(s_1 + s_2 = 2)$, if $s = [s_1, s_2]$ sparse, at least one of them needs to be s_x equal to 0; that is to say, by calling the sparse constraint, the number of solutions that can be solved is from infinity to two: $[s_1, s_2] = [2, 0]$ or [0, 2]. Since the norm counts the number of nonzero entries in the majority vector, the function is facilitated by sparsity, so the problem of finding the most redundant input vector among the measured vectors can be expressed as the following equation:

$$\hat{s} = \arg\min\|s\|_0 \quad \text{s.t } y = Hs. \tag{5}$$

In equation (5), $\|.\|_0$ means to find the zero norm, that is, the number of nonzero items. The equation is optimized according to the existing literature, see the following equation:

$$\hat{s} = \arg\min\|s\|_1 \quad \text{s.t} \quad y = Hs. \tag{6}$$

In equation (6), $\|.\|_1$ represents the sum of the absolute values of the nonzero components.



FIGURE 1: General principle model of the compressed sensing system.

3.2. Steps and Models of Improving the SWOMP Algorithm for the Communication Technology System. Using the abovementioned model, it can be found that the transformation and recovery of compressed sensing are a problem of seeking an optimal solution. On this basis, the improved algorithm SCWOMP is reconstructed. First, the principle of the improved algorithm is mastered. The piecewise approximation method has evolved from the earliest sparse adaptation. Entering the next stage, this step size is unchanged. The set step size is estimated until the iteration produces a residual greater than or equal to the residual of the previous iteration, as shown in the following equation:

$$\|r^k\|_2 \ge \|r^{k-1}\|_2.$$
 (7)

In equation (7), r represents the residual value, k represents the number of iterations, and $\|\cdot\|_2$ represents the sum of nonzero items. When equation (7) is satisfied, it means that the current step size will not reduce the margin any more, and there will even be an error in the estimator due to the relationship between the step sizes. Then, the approximate step size needs to be updated, see the following equation:

$$stage = stage + 1.$$
 (8)

In equation (8), stage represents the step size before updating and stage represents the updated step size. Different strategic ideas are used to increase complexity by switching the selection criteria when certain conditions are met, as shown in the following equation:

$$T_h = \alpha^* \max \left| \Phi^T r \right|. \tag{9}$$

In equation (9), $\alpha \in (0, 1)$, *T* represents the large step size, and *h* represents the number of step size iterations. There is the literature to prove that the $\alpha = 0.5$ recovery probability is the best, so the first weak selection of the study directly selects coefficient 0.5. Another criterion is the principle of selecting the largest correlation column in the later stage of the iteration, that is, the precise iteration with small step size. Both stages retain the fast recovery characteristics of the SWOMP algorithm and avoid overestimation when iterating to the actual ground truth. This completes the first atomic column selection of each iteration of the improved algorithm. Then, a second filter is added to prune candidate sets containing staggered columns with weak threshold selection, specifically not being able to backtrack every iteration. If there is no support set that can contain all the correct atoms, then $\Lambda_T \in \Lambda_t$ the relationship between them is shown in the following equation:

$$\Lambda_T - \Lambda_t \neq \phi. \tag{10}$$

In equation (10), Λ_T represents the correct candidate set, Λ_t represents the candidate set of the *t*th iteration, and ϕ represents the empty set. Equation (11) is explained for the superposition vector of the estimated signal ε :

$$x\Lambda_t = x\Lambda_T + \varepsilon. \tag{11}$$

During the process, the appearance of the noise vector interferes with the size of the original value, and the calculation will also be interfered during backtracking. Therefore, in order to ensure the effect of backtracking, the number of atomic columns in the support set needs to be limited, and sparsity begins to be reduced. We make the set value greater than or equal to sparsity and backtrack when the condition is met. The selection of the second weak threshold is specifically expressed as the following equation:

$$|\theta_i| \ge T_g = g \cdot \max |\Phi_{\Lambda t}^T r| \quad \text{while } ||\Lambda_t||_0 \ge K.$$
 (12)

In equation (12), $\forall i = J$ represents the set of serial numbers in the *g* sensing matrix selected for the first time in the process, Φ represents the coefficient, and the numerical range is in (0, 0.5]. Even if the backtracking process is added in the calculation process, the redundant and unnecessary number of iterations can be removed by secondary selection, and the signal can be recovered quickly by increasing recovery probability. The flowchart of the improved algorithm (SCWOMP) is shown in Figure 2.

The SCWOMP algorithm flow steps in Figure 2 are as follows: at the beginning, we input the number of sampling points, set the sensing matrix and the sparsity range, then carry out different planning of the standard, and start the calculation; after completion, we select the calculation of the second standard and take the maximum value corresponding to the footmark, which is stored in support Jining for sequence update. The least squares solution is solved in turn. If it meets the requirements of the equation, we go to the next step; if not, we return to step 2. We update the calculated residuals, analyze the value, and judge whether the result meets the conditions. If so, we output the final output θ_t . If not, we then judge whether it meets the criteria and conditions of the transformation selection. The final process ends [18-20]. During the operation of the SCWOMP algorithm, although a backtracking process has been added, which involves an additional least squares estimation step per iteration compared to OMP and SWOMP algorithms, secondary selection through appropriate thresholds can reduce the number of iterations and enable faster signal recovery. Therefore, in the case of little change in operation time, the recovery probability can be improved. In the comparison experiment of the algorithm, if the error and complexity are required to be calculated, the complexity



FIGURE 2: SCWOMP algorithm flowchart.

of the matching tracking class is shown in the following equation:

$$O(MP) = K + O(msl).$$
(13)

In equation (13), K represents the number of iterations, m represents the number of matrix rows used for observation, s represents the sparsity, and l represents the calculation bit accuracy. The SCWOMP algorithm is applied in a MIMO system, starting from a basic model, where the target signal is transmitted through a linear channel with additive white Gaussian noise (AWGN). The input-output relationship of the model is shown in the following equation:

$$y = Hs + v. \tag{14}$$

In equation (14), *y* represents the vector of the received signal, *H* represents the system matrix, satisfying $H \in C^{m \times n}$, *s* represents the expected signal vector, and *v* represents the noise vector, obeying $v \sim N(0, \sigma^2 I)$. In actual cases, it is more likely that the expected signal is not sparse, so cardinality can be selected ψ_i to represent the signal as a linear combination of cardinality. Using a suitable fundamental matrix $\Psi = [\psi_1 \cdots \psi_n]$, the input vector can be expressed as $s = \sum_{i=1}^n x_i \psi_i = \Psi_x$, and the input-output relationship evolves into the following equation:

$$y = Hs + v = H\Psi x + v. \tag{15}$$

In equation (14), x is the representation in the Ψ domain s. In the process, the original nonsparse vector can be s replaced with a sparse vector by properly selecting the cardinality domain x. This method of replacement does not change the model of the system. Combined with the algorithm equation mentioned above, the improved GSM-MIMO symbol detection algorithm uses the mechanism of the SCWOMP algorithm to detect the active antenna position set in network communication and combines with the MMSE algorithm to improve a more suitable system

detection algorithm. As described in the literature, since the steps of the OMP algorithm keep these error sequences, the detection performance is low, so on the basis of the aforementioned equation, equation (12) is rewritten in the MIMO system modulation communication system, see the following equation:

$$\left|\theta_{i}\right| \geq T_{g} = g \max_{T} \left\{ \left|\Phi^{T}r\right|, \Gamma \in S \right\}.$$

$$(16)$$

In equation (16), *S* represents the modulation constellation set. Then, we use MMSE to detect the reserved and closest antenna that satisfies the spatial symbol as the spatial symbol detection value. The specific flowchart is shown in Figure 3.

4. Performance Comparison and Simulation Analysis of SCWOMP in Communication System Symbol Detection

4.1. Performance Comparison of Different Compression Aware Reconstruction Recovery Algorithms. In order to demonstrate the performance superiority of the algorithm proposed by the research institute, the StOMP algorithm, OMP algorithm, and SP algorithm were selected to compare their performance with the SCWOMP algorithm constructed by the research institute at different sampling points [21–23]. Experiments were performed using the Gaussian sparse signal, set signal length N=256, and tested once at 5s intervals. The measurement matrix of the experiment is an $M \times N$ Gaussian random matrix, and the iterations are performed 1000 times. We calculate the reconstruction probability if the reconstruction error is less than 1×10^{-6} , and it means that reconstruction is successful. The simulation results are shown in Figure 4.

It can be found in Figure 4 that, with a gradual increase in the number of sampling points, the recovery probabilities of various algorithms begin to increase at different rates.



FIGURE 3: Flowchart of the improved SWOMP detection algorithm.



FIGURE 4: Performance comparison of different sampling points under different compressed sensing recovery algorithms.

Among them, when the number of sampling points is 60, the CoSaMP algorithm has a relatively large increase in the recovery rate. This is because the number of backtracking times set in the backtracking process of the fixed number of atomic columns of the algorithm is less, so the recovery probability in the process will have a big improvement. Other algorithms also have error atomic columns, and the recovery probability also has the opportunity to improve. During the operation of the system, the recovery probability of the StOMP algorithm and SP algorithm shows a high degree of coincidence. When the number of sampling points is 90, the recovery probability of both algorithms tends to 1. The recovery probability of the SCWOMP algorithm is the best. Many researchers choose to go back one step of the iterative result and adjust the step size when overestimating, so as to avoid overestimating the atomic column selection. When the number of sampling points is 80, the SCWOMP algorithm and the fixed steps are different but all reach the maximum recovery rate at this moment. When the number of sampling points is about 72, the recovery rate of SCWOMP is almost 1. The rate is faster than that of other algorithms. Then, the influence of sparsity on the recovery rate of the algorithm is described, as shown in Figure 5.

Figure 5 shows a performance comparison diagram of different sparsity under various compressed sensing recovery algorithms. It can be found that the recovery rates of all algorithms start to decrease at different rates as sparsity increases. Among them, the CoSaMP algorithm represented the fastest decline, and the recovery rate dropped to nearly 0 when sparsity was around 50. However, the recovery rate of the OMP algorithm, StOMP algorithm, and SP algorithm starts to decrease slowly with an increase in sparsity, and when sparsity reaches 60K, the reduction is close to 0. When the recovery probability of the StOMP algorithm and SP algorithm is 0, the corresponding sparsity values are 55 and 65, respectively.

When the SCWOMP algorithm has a fixed step size of 5, as sparsity increases, the slope corresponding to the recovery rate curve is larger than that of other algorithms, indicating that the rate of reduction in the recovery probability is slower than that of other algorithms. We conducted an experiment with different step sizes of the SCWOMP algorithm. In the experiment, we try to set a more appropriate threshold value and filter multiple atomic columns to reduce the number of iterations. It can be seen from the results that the same sparsity can achieve better than other algorithms' recovery rate.

4.2. Simulation Analysis of the Improved Compressed Sensing Recovery Algorithm. The experimental parameter settings are the same as in Figure 4. The SCWOMP algorithm is used to compare the simulation with other algorithms under different coefficients, 1000 times, and the reconstruction probability is calculated. When the reconstruction error is less than 10^{-6} , the reconstruction is successful. The experimental simulation results are shown in Figure 6.

In Figure 6(a), the sparsity is set to 20. During the process, the influence of the recovery probability is observed when the measurement value changes and the ordinate corresponds to the reconstructed power of the signal. It can be found that, in the process of increasing the number of sampling points, the recovery probability under all algorithms begins to increase, and the SCWOMP algorithm has a higher recovery probability than other algorithms. When the pruning coefficient g = 0.5 and the number of sampling points is 80, the reconstruction rate has a maximum value. The recovery probability also increases with the pruning factor. M, when the other three algorithms reach the maximum reconstruction probability, is significantly larger than that of the SCWOMP algorithm. In Figure 6(b), the measurement value is set to 130. During the process, the influence of the change of sparsity on the recovery



FIGURE 5: Performance comparison of different compressive sensing recovery algorithms with different sparsity.



FIGURE 6: Variation of recovery probability with different (a) measurements and (b) sparsity.

probability is observed and the ordinate corresponds to the reconstruction probability. With an increase in sparsity, the rate of reduction of the reconstruction probability of the SCWOMP algorithm is significantly lower than that of other algorithms, and when sparsity reaches 70, the reconstruction probability becomes 0, which indicates that the proposed algorithm has a wider range of reconfigurable range. The simulation trial used two different sets of the original signals: (1) $f = \cos (2 \pi /$ 256 t) + sin(2 $\pi/128 \, t$) and (2) $f = 0.3\cos(\theta)$ $(2 \pi \times 0.625 t) + 0.6sin (2 \pi \times 0.125 t)$; signal sparsity uses the discrete cosine transform (DCT) method. The trim coefficient is set to 0.5. Using the proposed SCWOMP algorithm, the comparison between the recovered signal and the original signal waveform is plotted in Figure 7.

In Figure 7, the red curve represents the recovered waveform and the blue curve represents the original waveform. Observing the frequency domain, it can be found that the main components of the signal of the proposed algorithm are gradually recovered in the process. By comparing the red recovery waveform with the blue original waveform in two phases, the SCWOMP algorithm can repair the original signal within a certain error range. Through the matching pursuit algorithm, it can be known that the difference in the overall calculation amount is mainly related to the difference in the number of iterations. Using a two-harmonic signal in the OMP algorithm, the CoSaMP algorithm are compared in the simulation of the number of iterations and the error margin, as shown in Figure 8.



FIGURE 7: Comparison of two groups of improved algorithm recovery waveforms and original waveforms.



FIGURE 8: Changes in error margins of different algorithms under different iterations.

In Figure 8, it can be found that the proposed SCWOMP algorithm can reach the minimum error margin value faster than the OMP algorithm, avoiding unnecessary step size changes, but it can be closer to the performance of the OMP algorithm. When the OMP algorithm reaches almost the same error margin as the CoSaMP algorithm, 70 iterations are required; by using the improved algorithm proposed in the study, it can not only achieve excellent performance in a short time but also can perform fewer iterations than the OMP algorithm. The improved algorithm in the figure can

TABLE 1: Complexity comparison.

Algorithms	Complexity	
	NA = 2	NA = 3
ML	122579	172052
MMSE	24856	25009
ZF	10284	10113
OMP	2056	2701
SCWOMP	4289	4627

achieve the effect of 100 iterations of the OMP algorithm when it performs about 10 iterations. This again proves that the improved algorithm has the excellent performance of the other two algorithms and can make the recovery performance significantly improved. Finally, in order to ensure that other advantages of compressed sensing have an impact on the bit error rate of the algorithm, first, we contrast their complexity, as shown in Table 1.

It can be seen from Table 1 that the complexity of the proposed algorithm is quite consistent with the theory, and the complexity of the ML algorithm is the highest, the complexity of the OMP algorithm is the lowest, and the proposed algorithm is lower. Since the communication system will be affected by the surrounding environment and noise in the process of operation, the system analyzes the bit error rate of signal transmission in the process of the change in a signal-to-noise ratio of different algorithms, see Figure 9.

Figure 9 shows the trend diagram of the bit error rate (BER) of the ML, ZF, MMSE, and OMP algorithms and the improved algorithm in the process of changing the signal-to-noise ratio. The BER of the proposed algorithm is lower than that of the ZF algorithm, MMSE algorithm, and OMP algorithm in the process of change and can also be closer to the performance of the excellent ML algorithm. When the signal-to-noise ratio is 10 dB, there is a minimum bit error



FIGURE 9: Trend plots of BER changes with SNR for different algorithms.

rate of about 10^{-3} . Although all algorithms using compressive sensing reconstruction have floor effects, the proposed algorithm has significantly lower floor effects.

5. Conclusion

The 5G era is about to enter, and modern society has never stopped exploring the advantages of MIMO technology. The research proposes the SCWOMP algorithm. First, we compare the performance of different sampling points and sparsity under various compressed sensing recovery algorithms; then, we compare the recovery probability of the improved algorithm and other algorithms when the measured value and sparsity are different and the performance of the improved algorithm under different original waveforms. The recovered waveforms are compared with the algorithm's error margin and performance changes. The results show that the increase in sparsity reduces the reconstruction probability of the SCWOMP algorithm at a significantly lower rate than other algorithms. By setting the trim coefficient to 0.5, the original waveform in the frequency domain can be repaired within a certain error range through the operation of the algorithm. When calculating the error margin of the algorithm with different iteration times, the proposed algorithm can reach the value of the minimum error margin faster than the OMP algorithm and can avoid unnecessary step size changes. The final result shows that the SCWOMP algorithm is performing. The best performance can be achieved after about 10 iterations. Comparing the SNR with many algorithms, when the SNR reaches 10 dB, there is a minimum bit error rate, which is about 10^{-3} , and the existing floor effect is the lowest. All of these prove that the overall performance of the proposed algorithm is optimal, which can be of great help to the communication system technology. However, there are very few studies on the combination of compressed sensing and segment

backtracking at present. The follow-up expansion of the research scope and the use of the advantages of the algorithm to extreme are still the direction that can be continued to be explored.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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