Compressed Sensing Based Approach for Sparse Signal Reconstruction and User Activity Detection

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Abstract—**The escalating demand for wireless connectivity and the proliferation of Internet of Things (IoT) devices have driven the exploration of new techniques to enhance the capacity and efficiency of wireless communication systems. In this context, the integration of grant-free uplink Non-Orthogonal Multiple Access (NOMA) with compressed sensing for active user detection has seen increased prominence. This paper presents a comprehensive overview of this emerging approach. By leveraging the principles of NOMA, multiple users can efficiently share the same time-frequency resources, improving spectral efficiency. Compressed sensing techniques are used to detect active users by capitalizing on the sparse nature of user activity. This reduces computational complexity along with increasing the real-time processing capabilities, especially in scenarios with high user density. The synergy between grant-free uplink NOMA and compressed sensing holds promise for addressing the challenges of modern wireless communication systems, including IoT networks and smart cities. Utilizing this idea, we introduced sparsity induced compressed sensing mechanism for activity detection, and symbol reconstruction. This approach is found to achieve enhanced performance in parameters - probability of detection, NMSE, and symbol error rate as shown by experimental analysis.**

Index Terms—**Grant free NOMA, Compressed sensing, activity detection, sparsity.**

I. INTRODUCTION

With the advancements in wireless communication technology, the use of wireless devices has increased manyfold and it is expected to top 500 billion devices by 2024 [1]. The significant surge in the number of devices supporting wireless communications presents many obstacles in fulfilling performance demands, encompassing aspects like enhanced spectral efficiency, extensive connectivity, minimized power consumption, exceptionally reliable communication, and communication systems with exceedingly low latency. Throughout the evolution of wireless communication, multiple access has emerged as a pivotal technology distinguishing various wireless system generations [2]. For instance, 1G employed FDMA, 2G utilized TDMA, 3G embraced CDMA, and 4G adopted OFDMA [3]. These come under traditional orthogonal multiple access (OMA) techniques, adhering to the principle of orthogonal resource allocation to mitigate or eliminate interference among users. This characteristic enables straightforward signal detection through uncomplicated receivers. Nevertheless, the scope of users that OMA can accommodate is confined by the availability of orthogonal resources, posing challenges in fulfilling the expansive connectivity demands of 5G [4].

Therefore, presently NOMA concept has garnered great attention within the perspective of next-generation communications due to its potential for increased total data rates. NOMA allows many users to share same or similar frequency, time, or code resources [5]. Essence of NOMA lies in its allocation of non-orthogonal resources to users, facilitating system overloading—a mechanism that enhances users' ability to efficiently share the same resources. Implementation of advanced multiuser detection

(MUD) techniques help in effectively separating user signals at the receiver. NOMA schemes are broadly categorized into two as power and code domain NOMA. Extensive research has been undertaken on NOMA in existing literature, focusing on objectives like maximizing the cumulative data rate [6], minimizing power consumption [7] and probability of signal-to-interference-plus-noise ratio (SINR) outage [8]. In pursuit of these goals, a range of techniques has been proposed, including cooperative NOMA [9], and power management strategies [10].

Within code domain NOMA, to distinguish various users at the receiving end, different user-specific codes serve as access signatures. However, due to lack of resources compared to the total user count, these codes inherently lack orthogonality to one another. Several code-domain NOMA methods have been discussed in literature such as pattern division multiple access (PDMA) and sparse code multiple access (SCMA) which work on codebook-based approach where a unique code book is assigned to each user. Within the framework of power domain NOMA, users are allocated distinct power levels that facilitate their utilization of the accessible resources—whether they pertain to time, frequency, or code allocations [7, 8]. In multiuser detection, to distinguish users based on their allotted power levels, the receiver employs successive interference cancellation (SIC). However, during the data transmission in NOMA system, the data is analyzed in time and frequency domains. At this stage cancellation of interference and recovering the optimal transmitted data becomes a challenging issue. Several multiuser detection-based methods have been developed such as message passing algorithm (MPA), Asynchronous multi-user detection for code-domain NOMA [11], maximum likelihood-based MUD in uplink NOMA [12] and SIC based MUD etc. [13]. These techniques, however, suffer from computational complexities. Moreover, aforementioned essentially require users to obtain permission for accessing them. This implies that both the base station (BS) and users have to share a significant volume of pilot signals to facilitate user access. This process results in impractical training overhead and substantial latency [15]. Hence, need is growing for a user access-based method in NOMA systems that offers minimal overhead and low latency.

Generally, the traditional uplink wireless communication systems work on the concept of request-grant procedure to establish and accomplish the communication. However, this process leads to increase in the signaling overhead and latency which is not suitable for 5G and advanced communication scenarios. Therefore, grant-free communication processes are envisaged as a breakthrough in wireless communication systems. Particularly, the idea of grant-free transmission, where multiple users can send data without the requirement of a rigid access granting process, is gaining traction. This can be effectively realized through user activity detection (UAD) at the BS. However, the inherent randomness of user activity during a given time slot, coupled with the BS's inability to access information regarding user activity without the request-grant method, poses a significant challenge for Multi-User Detection (MUD). During a given time slot, the count of active users is typically much lower compared to the total possible users in the system, even during peak usage periods [16]. This situation transforms the MUD challenge into a problem of recovering sparse signals. Various approaches based on the principles of Compressive Sensing (CS) have been suggested to address this, as outlined in prior research [17].

Similarly, the allocated transmission bandwidth has undergone a progression, expanding from 200 kHz in the 2G GSM system to 5 MHz in 3G, and reaching a maximum of 20 MHz in 4G. Concurrently, the utilization of antennas has escalated from a single antenna in 2G/3G systems to eight in 4G, alongside a rising concentration of deployed BSs and supported users. In spite of the progressive growth in bandwidth, antenna count, and the density of both BSs and users, all preceding wireless cellular networks have been built upon the foundational Nyquist sampling theorem. This theorem asserts that a bandwidth-constrained signal can be accurately reconstructed as long as the sampling rate exceeds twice the signal's maximum frequency. However, the upcoming 5G advancements will demand a minimum bandwidth of 100 MHz, incorporate numerous antennas, and involve the ultra-dense deployment of BSs to accommodate the substantial user base. These qualitative shifts suggest that employing Nyquist's sampling theorem, as was done with the earlier 2G/3G/4G solutions, in the context of 5G techniques, could give rise to unparalleled challenge such as substantial overheads, impractical complexities, and elevated costs and/or power consumption due to the high number of samples needed. To this end, the compressive sensing is considered as a promising technique which facilitate a sub-Nyquist approach to reconstruct the sparse signals efficiently. By considering these advantages of compressed sensing, we leverage this approach for user detection in grant-free NOMA system.

1.1. Article Organization

Organization of the rest of the article is as follows: section 2 presents the complete description of proposed approach; section 3 presents the outcome of proposed approach and its comparative analysis with existing mechanisms and section 4 presents the concluding remarks of this research.

II. PROPOSED MODEL

This section introduces the proposed approach for detecting user activity and estimating the channel within an uplink code domain Non-Orthogonal Multiple Access (NOMA) system. Assume a communication setting in which an uplink grant-free NOMA system is established such that a BS is in communication with K distinct users. In this context, each of the K users is considered to be having a single antenna.

As discussed in the preceding section, the number of active users within the system is typically much lower than the total potential user count, even during periods of peak usage. As a result, only a small subset of active users is assumed. Following this methodology, for each active user, a pilot symbol is transmitted in the initial time slot to facilitate channel estimation. Subsequently, J data symbols are transmitted in the subsequent time slots. The process is illustrated in Figure 1 below, depicting the data transmission procedure for the uplink grant-free NOMA system.

In every frame, there are some active users which consist of pilot and data symbols which are distributed over N subcarriers. This distribution is done with the help of spreading sequence for each user. In order to establish an environment of massive connectivity, this method utilizes the non-orthogonal spreading sequence as $N < K$. Thus, the received signal at BS can be given as:

$$y_p = \sum_{k=1}^{K} h_k s_k p_k + n_p = S.diag(h)p + n_p \qquad (1)$$

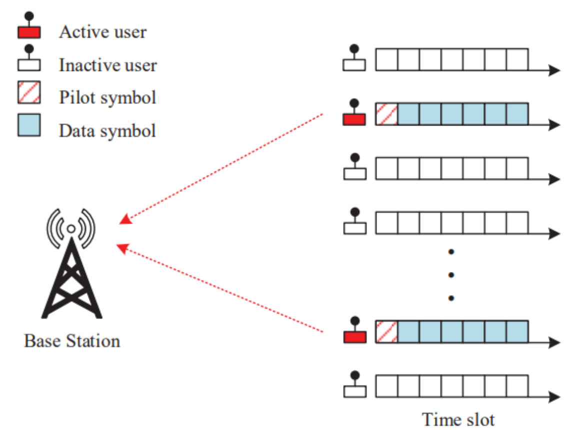

Fig. 1 Communication process for uplink grant-free NOMA system

Where $S = [s_1, s_2, \dots, S_K] \in \mathbb{C}^{N\times K}$ represents the spreading matrix, h_k is the channel gain between user k and BS where $h = [h_1, h_2, \dots h_K]^T \in \mathbb{C}^{K\times 1}$ this obeys the independent complex Gaussian distribution $\mathcal{CN}(0,1)$ and $p = [p_1, p_2, \dots, p_K]^T \in \mathbb{C}^{K\times 1}$ represents the vector of pilot symbols which is zero for inactive user, and $n_p \sim \mathcal{CN}\left(0, \sigma_p^2 I_N\right)$ represents the AWGN. At the receiver end, in j^{th} time slot duration, the received signal can be expressed as:

$$y_d^{(j)} = \sum_{k=1}^{K} h_k s_k x_k^{(j)} + n_d^{(j)} = S.diag(h)x^{(j)} + n_d^{(j)} \qquad (2)$$

Where $x^{(j)}$ represents the transmitted data symbol vector as $x^{(j)} = \left[x_1^{(j)}, x_2^{(j)}, \dots, x_K^{(j)}\right] \in \mathbb{C}^{K\times 1}$ at the given j^{th} time slot duration whereas the active user k during this time slot is presented as $x_K^{(j)}$ and their corresponding data symbol is obtained from the complex constellation set $\mathcal{X}$. However, as the inactivate users do not participate in symbol transmission, their transmitted symbol is zero. At this stage, the noise vector of each symbol can be given as $n_d^{(j)} \sim \mathcal{CN}(0, \sigma_d^2 I_N)$ and its equivalent complex constellation is characterized as $\widetilde{\mathcal{X}} \triangleq \{\mathcal{X} \cup 0\}$.

In this model we consider frame-wise symbol transmission along with sparsity. The sparsity models for the frame-wise transmission can be expressed as:

$$supp(x_p) = supp(x^{(1)}) = \cdots = supp(x^{(J)}) = \Gamma \qquad (3)$$

Where Γ represents the active user count and $|\Gamma|$ is the total user count. However, the spare nature of data and its transmission over a channel affects the data transmission. Therefore, data received is stated as:

$$Y = SA + N \tag{4}$$

Where $Y = [y_p, y_d^{(1)}, \dots, y_d^{(J)}] \in \mathbb{C}^{N\times(J+1)}$, $A = diag(h).[p, x^{(l)}, \dots, x^{(J)}] \in \mathbb{C}^{K\times(J+1)}$ and $N = [n_p, n_d^{(1)}, \dots, n_d^{(J)}] \in \mathbb{C}^{N\times(J+1)}$. The main objectives of the work are to perform channel estimation, activity detection and data detection. This can be accomplished by recovering the signal A based on signal Y. To achieve this, we introduce sparse compressed sensing approach and transform the reconstruction problem which is expressed as:

$$b = Dc + v \tag{5}$$

Where $b = vec\,(Y^T) \in \mathbb{C}^{N\,(J+1)}$, $D = S \otimes I_{(J+1)} \in \mathbb{C}^{N(J+1)\times K(J+1)}$, $c = vec(A^T) \in \mathbb{C}^{K(J+1)\times 1}$ and $v = vec\,(N^T) \in \mathbb{C}^N$. Generally, the traditional algorithms suffer from computational complexity issues which need to be addressed moreover existing methods ignore the sparse structure of transmitted signal which affects the signal reconstruction. To overcome this, we have presented gradient vector formulation-based approach which helps to identify the non-zero position in transmitted sparse signal. Moreover, this approach doesn't require any sparse level information. The complete approach is divided four phases: phase 1 initializes the complete process where various parameters are initialized to generate the sparse structure. In step 2 it performs several iterations which includes estimating the support, computing the gradient, estimating the signal and update the signal. Similarly, step 3 obtains the estimated support and updates the signal, support and sparsity levels. Finally, it obtains channel coefficient and data symbols and recovers the signal. Below given algorithm 1 describes the complete process.

Algorithm: Proposed algorithm for Sparse Compressed Sensing
Input: Received signal Y, spreading sequence S, time slots Output: channel estimation $\hat{h}$, reconstructed signal
Step 1: Initialize parameter generation process 1. Generate sparse data block $b = vec(Y^T), D = S \otimes I_{J+1}$ 2. Initialize different parameter: iteration count, support $\Gamma^{(t-1)} = \phi$, initial sparsity level, sparse signal $c^{(t-1)} = 0$, and residual vector $r^{(t-1)} = b$ Step 2: Initialize the Iteration Count 3. Compute relationship as $corr^{(t)} = D^H r^{(t-1)}$ 4. Estimate the support by using correlation: $\hat{\Gamma}^{(t)} = \Gamma^{(t-1)} \cup \max(\lvert cor[k]\rvert, 1\rvert), k = 1,2,\dots,K$ 5. Compute gradient $g^{(t)}[\hat{\Gamma}^{(t)}] = cor^{(t)}[\hat{\Gamma}^{(t)}], g^{(t)}[\{1,2,\dots,K\}\,\hat{\Gamma}^{(t)}] = 0$ 6. Update $a_{opt}^{(t)} = \frac{(r^{(t-1)})^H.(D[\hat{\Gamma}^{(t)}].g^{(t)}[\hat{\Gamma}^{(t)}])}{\lVert D[\hat{\Gamma}^{(t)}].g^{(t)}[\hat{\Gamma}^{(t)}]\rVert_2^2}$ 7. Perform signal estimation as $\tilde{c}^t[\hat{\Gamma}^{(t)}] = c^{(t-1)}\left[[\hat{\Gamma}^{(t)}] + a^{(t)}.g^{(t)}[\hat{\Gamma}^{(t)}]\right]$ 8. If $\min\left\{\lVert\tilde{c}^{(t)}\,[m]\rVert_2^2\right\} \le (J+1).V_{th}$ is breached then Break 9. End \iteration 10. Update residue using $r^{(t)} = r^{(t-1)} - a_{opt}^{(t)}.D[\hat{\Gamma}^{(t)}].g^{(t)}[\hat{\Gamma}^{(t)}]$ 11. Update signal, support and corresponding levels of sparsity $c^{(t)} = \tilde{c}^{(t)}, \Gamma^{(t)}$ and $s = s + 1$ Step 3 Estimate the support 12. Estimate the support as $\Gamma_s = \Gamma^{(t-1)}$ Step 4 Obtain coefficients and symbols 13. Recover the sparse and block data $c[\Gamma_s] = (D[\Gamma_s])^\dagger b, \hat{c}[\{1,2,\dots,K\}] = 0$ 14. Recover signal $(\mathcal{A}) = [vec^{-1}(\hat{c}, J+1)]^T$ 15. Estimate the channel coefficients as $\hat{h} = \hat{A}\,(:,1)$ 16. Obtain data symbol as $x^j = diag\,(1./\hat{h}) \times \hat{A}(:,j), j = 2,\dots,J+1$

III. RESULTS AND DISCUSSION

This section presents the outcome of proposed approach and its performance is compared with existing schemes. In this simulation scenario, we have considered total number of users $K = 256$ whereas active users are considered as 25 in each frame. Moreover, we have used Golay spreading(DSSS) sequence with $N = 128$ and employed the QPSK modulation scheme. Each data frame has 7 consequent symbol duration. We compare the performance by way of successful activity detection, Normalized Mean Square Error.

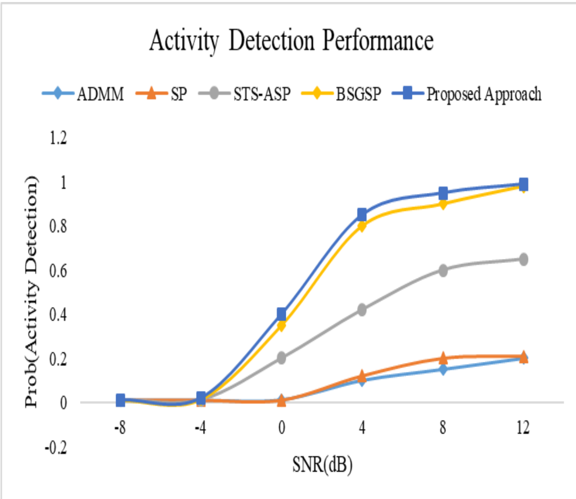

Fig. 2 Performance of Activity Detection

Performance of the proposed approach is demonstrated, as given in fig. 2 above, in terms of probability of activity detection. Higher probability establishes the better performance. According to this experiment, the proposed approach obtained the average detection performance as 0.56766 whereas the existing methods such as ADMM, SP, STS-ASP, and BSGSP reported their average detection performance as 0.0803, 0.0933, 0.315, and 0.5093, respectively which shows that the proposed approach obtained better performance. Similarly, we measured the performance in terms of NMSE for varied SNR values. Below given figure 3 demonstrates the obtained performance and its performance is compared with aforementioned existing schemes.

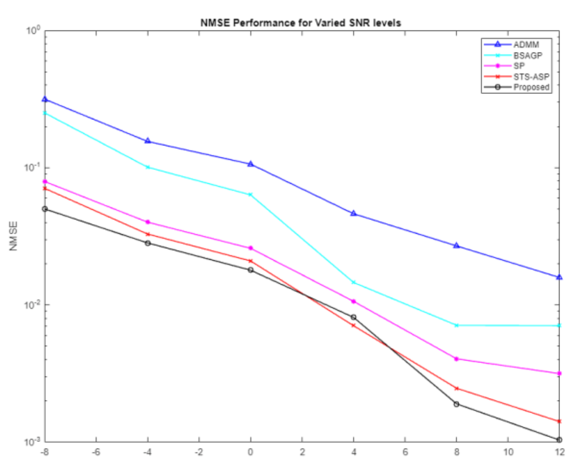

Figure 3 NMSE Performance

The NMSE performance is computed as $\frac{\|h-\hat{h}\|_2^2}{\|h\|_2^2}$ the proposed approach reported better performance whereas existing schemes suffers from NMSE issues due to inappropriate detection and reconstruction leading to poor precision of gradient. The experimental analysis shows that the average NMSE is obtained as 0.0912, 0.0540, 0.0221, 0.0177, and 0.0151 by using ADMM, BSAGP, SP, STS-SSP and proposed approach respectively.

Further, we measured the performance through symbol error rate and compared the thus obtained performance with existing schemes. Below given figure depicts the outcome of this experiment.

In this approach the proposed approach obtained better performance proposed sparse mechanism and identical behavior of channel coefficients at all subcarriers. The average performance is obtained as 0.1146, 0.0404, 0.0170, 0.0228 and 0.0135 by using ADMM, BSAGP, SP, STS-SSP and proposed approach respectively.

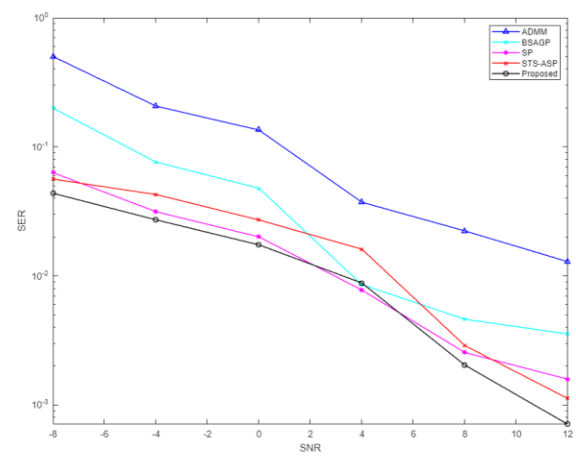

Figure 4 SER performance for varied SNR levels

IV. CONCLUSION

Combining grant-free uplink NOMA with compressed sensing while achieving active user detection holds significant promise in advancing the efficiency and capacity of modern wireless communication systems. This innovative approach addresses the challenges posed by the explosive growth in connected devices and the increased demand for higher data rates. Following the principles of NOMA, many users can share the same time-frequency resources concurrently, enhancing the overall performance. The incorporation of compressed sensing techniques for active user detection further enhances the overall system performance. By exploiting the sparse nature of user activity, compressed sensing reduces the need for exhaustive searches and complex signal processing, thereby reducing computational complexity and improving real-time processing capabilities. This results in quicker and more accurate identification of active users in grant-free scenarios, even in scenarios with high user density.

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