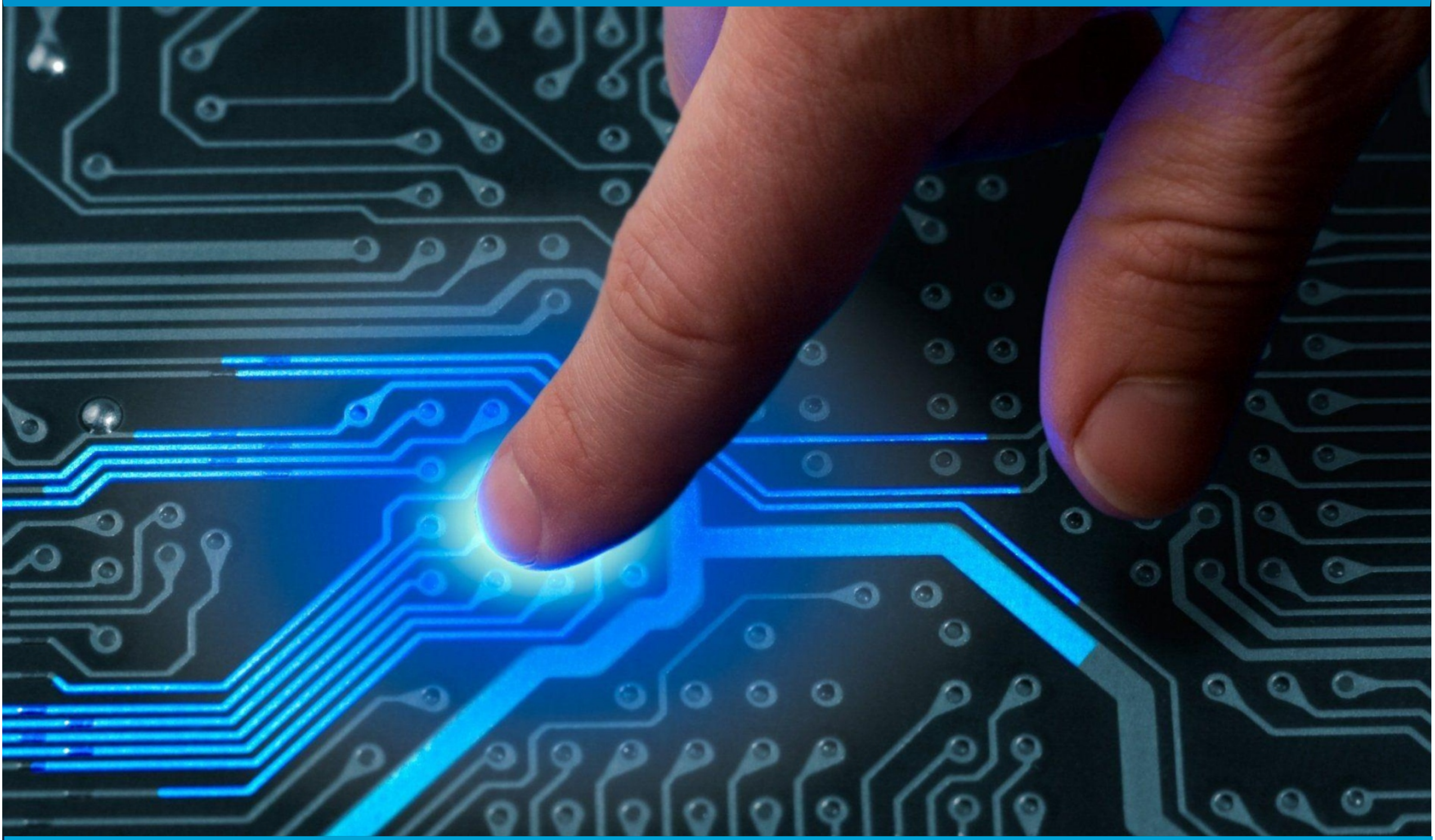

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Block Sparse Recovery System Using Advanced BSBL Joint User Activity Detection and Channel Estimation for NOMA Systems

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ABSTRACT:-This paper concerns uplink grant-free non orthogonal multiple access, where the handshaking procedure is not required to reduce control signaling overhead and transmission latency. The joint UAD and CE is formulated as a block sparse signal recovery problem. First, the compressive sampling matching pursuit (CoSaMP) algorithm is used for solving the electromagnetic inverse scattering problem on two-dimensional sparse domains. Then, block sparse Bayesian learning (BSBL) is investigated to solve this problem, and in particular a low complexity message passing based implementation of BSBL with belief propagation and mean field is developed. The proposed message passing based BSBL (MP-BSBL) algorithm has a complexity independent of active user number, which can be significantly lower than that of the CoSaMP algorithm. In addition, MP-BSBL provides an estimate of the noise power, which can be readily used for data detection.

I. INTRODUCTION

That's been shown that the conventional orthogonal multiple access (OMA) techniques, where each orthogonal resource block serves a single user, are spectral inefficient to meet the demands on high throughput, low latency, massive connectivity for the fifth generation (5G) wireless communications. Non-orthogonal multiple access(NOMA), where a resource block is used to serve multiple users, is considered a promising technology to fulfill these requirements, e.g., in enhanced mobile broadband (eMBB), ultra-reliable low latency communication (URLLC), and massive machine type of communication (mMTC). In addition, mMTC and URLLC are mainly for severing Internet of Things (IoT), which has the characteristics of massive connections and sporadic transmissions (users access the network randomly to transmit small data packets). The handshaking between base station (BS) and active users in the conventional grant-based network leads to large signaling overhead and high transmission latency, which are unacceptable in mMTC and URLLC as the communication becomes inefficient due to the small amount of payload data. Therefore, grant-free transmission without handshaking procedure is highly desirable, where users can randomly transmit data at any time slot and active users have to be identified by BS before data detection. According to the mobile traffic statistics reports, even in the busy hour, only a small fraction of users transmit data simultaneously and the active user number does not exceed 10% of the total number of users served by a network. Hence, the distribution of active users in uplink grant-free NOMA is sparse, which inspires the formulation of user activity detection (UAD) and multi-user detection (MUD) under the compressive sensing (CS) framework, a CS-MPA detector is proposed for uplink grant-free NOMA system, where the compressive sampling matching pursuit (CoSaMP) algorithm is used to detect user activity, and data detection based on a message passing algorithm (MPA) is then performed for active users. By assuming the active user set is unchanged during several continuous time slots of a frame, a joint MUD algorithm based on approximate message passing (AMP) and expectation maximization (EM) is proposed by using the prior information of the transmitted discrete symbols. In

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addition, by considering the temporal correlation relationship among different time slots, a dynamic compressive sensing (DCS)-based multi-user detector using orthogonal matching pursuit (OMP) and a prior-information aided adaptive subspace pursuit (PIA-ASP) algorithm are proposed to detect user activity and transmitted signal in several continuous time slots.

Algorithm: If the channel response (or channel transfer function) for a particular channel is H(s) then the input signal is multiplied by the reciprocal of it. This is intended to remove the effect of channel from the received signal, in particular the inter symbol interference (ISI).The zero-forcing equalizer removes all ISI, and is ideal when the channel is noiseless. However, when the channel is noisy, the zero-forcing equalizer will amplify the noise greatly at frequencies f where the channel response $H(j2\pi f)$ has a small magnitude (i.e. near zeroes of the channel) in the attempt to invert the channel completely. A more balanced linear equalizer in this case is the minimum mean-square error equalizer, which does not usually eliminate ISI completely but instead minimizes the total power of the noise and ISI components in the output.

BLOCK DIAGRAM

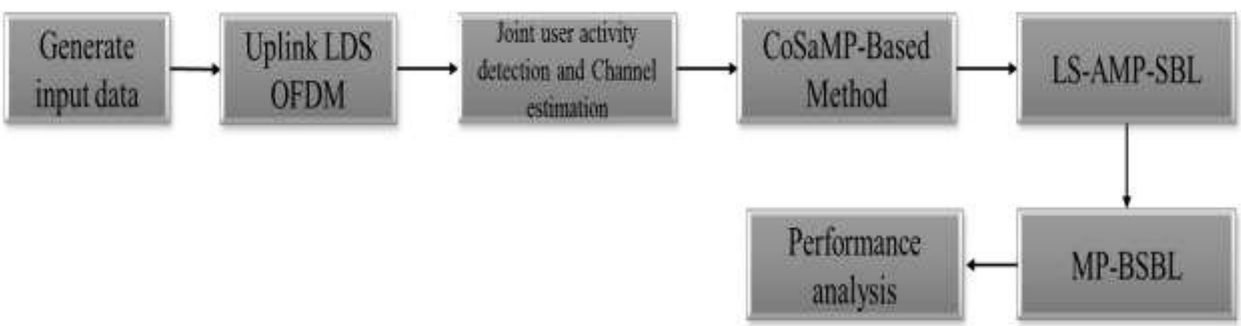

Fig . The block diagram of Proposed system

II. RELATED WORK

1. BOMP - Block Orthogonal Matching Pursuit

- In this iteration process continues until a stopping condition is achieved. Note that the ideal number of iterations is the block sparsity level K+ .
- The computational complexity of the BOMP algorithm is analysed, which grows rapidly with the fourth power of K+ . This can easily lead to an expensive cost even for a modest value of K+ (e.g., K+ = 25 in a NOMA system with 250 users and an active rate of 10%.).
- In the following, we investigate SBL based solutions. As the joint UAD and CE can be formulated as a block sparse signal recovery problem, we can solve it with the block sparse Bayesian leaning. We will develop an efficient inference algorithm to recover the block sparse vector $\bar{h}$ by using message passing.

2. MP-BSBL-Based Method

We employ a two-layer hierarchical structure, where the prior pdf of $\bar{h}$ is assumed to be
$p(\bar{h}) = \gamma\, p(\bar{h}|\gamma)p(\gamma)d\gamma$,
Where
$p(\bar{h}|\gamma)$ is a conditional prior pdf and
$p(\gamma)$ is a hyper-prior pdf.
Due to the block-sparse structure of $\bar{h}$, the elements of the k-th block can share a single hyper-parameter precision

3. CoSaMp Method

The compressive sampling matching pursuit (CoSaMP) algorithm is used for solving the electromagnetic inverse scattering problem on two-dimensional sparse domains. The major algorithmic challenge in compressive sampling is to approximate a compressible signal from noisy samples. Since the scattering matrix, which is computed by sampling the Green function, does not satisfy the restricted isometry property, a damping parameter is added to the diagonal entries of the matrix to make the CoSaMP work. The damping factor can be selected based on the level of noise in the measurements. It is likely to be extremely efficient for practical problems because it requires only matrix–vector multiplies with the sampling matrix.

IV. RESULTS AND DISCUSSION

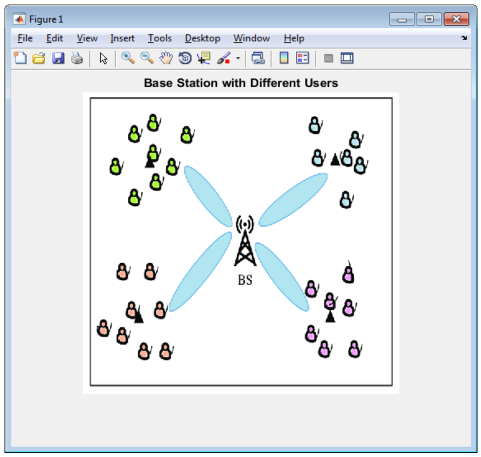

Fig1.

The network will be formed with the number of users as we assumed and that can be subdivided into four different sub-network. The formation of sub-network is based on the value of efficiency of transmission and the data rate. Fig 1.

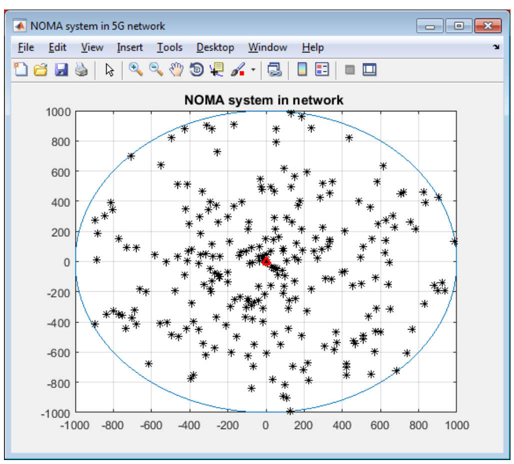

Fig 2.

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In this Fig 2 the NOMA system will be obtained with the specified range for the active user detection and the channel estimation for the active users. Based on the method of BSPL block sparse problem will be recovered. The range of NOMA system will be specified based on the baud rate.

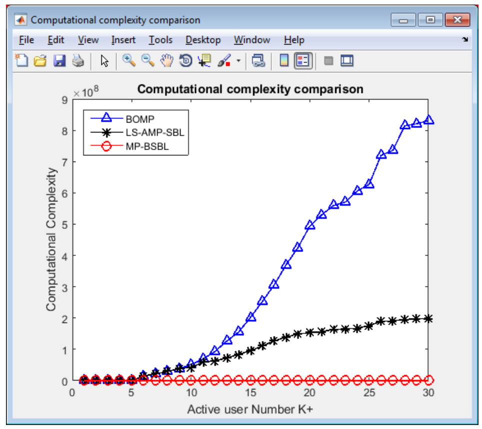

Fig 3.

The Computational complexity curve will be shown in fig 3., This is the comparison curve between the BOMP, LS-AMP-BSL and BSPL algorithm. The resulted curve shows that, the BSPL algorithm is suitable for message passing without the block sparse signaling.

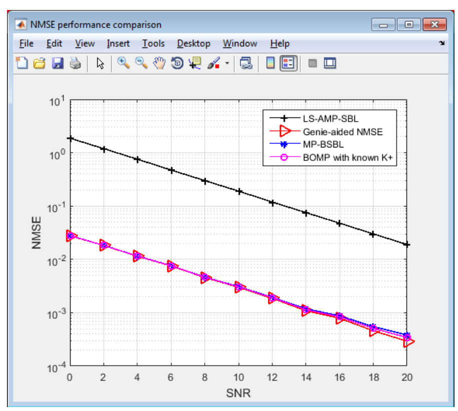

Fig 4.

In this Fig.4. shows that the comparison between Signal to Noise Ratio (SNR) and Normalized Mean Square Error(NMSE). When compared to the LS-AMP-BSL algorithm the BSPL and BOMP algorithm provides High SNR value and low NMSE.

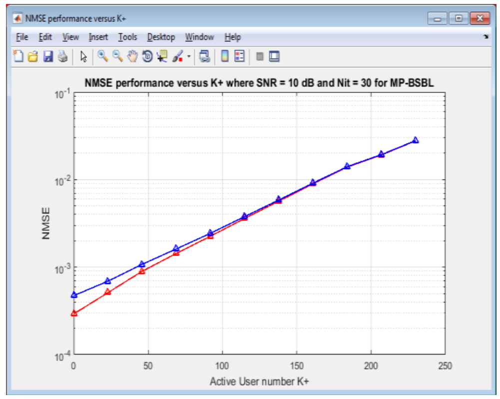

Fig 5.

In this Fig.5 shows the performance analysis for active users and the value of NMSE will be low when the active users increases. This will indicate the message passing from the transmitter module to the receiver have efficient transmission.

IV. CONCLUSION AND FUTURE WORK

In this paper, the joint user activity detection and channel estimation in grant-free NOMA systems to a block sparse signal recovery problem, and developed a low complexity message passing based block sparse Bayesian learning algorithm MP-BSBL to solve the problem. The LDS property has been fully exploited to reduce the complexity of the algorithm, and in particular, MP-BSBL is implemented efficiently with combined BP and MF message passing. It has been shown that MP-BSBL can reach the performance bound and significantly outperforms CoSaMP and LS-AMP-BP in terms of computational complexity and/or recovery performance. The value of NMSE and SNR of the system will be improved with the method of CoSaMp method for the active K+ users detection. The performance of the system will increases with the decreased value of error rate of the system. The complexity level of MP- BSBL method is low when compared to the previous work. So, the performance of the system also increases. In future, the level of system will be decreases and this will also increases the performance of the system.

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