Impulsive Noise Cancellation for MIMO-OFDM PLC Systems: a Structured Compressed Sensing Perspective

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***Abstract*—In this paper, a novel impulsive noise (IN) cancellation scheme based on structured compressed sensing (SCS) for multiple input multiple output orthogonal frequency division multiplexing (MIMO-OFDM) power line communication systems is proposed. The SCS theory is introduced to IN recovery for the first time in this paper to the best of the authors' knowledge, and the gap of lack of research on the IN mitigation for MIMO PLC systems is filled. First, the measurements matrix of the IN is obtained, and the SCS optimization framework is formulated through the proposed spatially multiple measuring method, by fully exploiting the spatial correlation of the IN signals at different receive antennas. To efficiently reconstruct the IN signal, an enhanced SCS-based greedy algorithm, structured *a priori* aided sparsity adaptive matching pursuit (SPA-SAMP), is proposed, which significantly improves the accuracy and robustness compared with the state-of-art methods. Theoretical analysis and computer simulations validate that the proposed scheme outperforms conventional methods in the typical MIMO PLC system.**

***Key words*—Impulsive noise, MIMO-OFDM, power line communication, structured compressed sensing (SCS), structured *a priori* aided sparsity adaptive matching pursuit (SPA-SAMP).**

I. Introduction

ORTHOGONAL frequency division multiplexing (OFDM) has been widely adopted in various broadband data transmission systems due to its high spectral efficiency and superior performance [1], [2]. More recently, the multiple input multiple output (MIMO) technique has been introduced to OFDM to achieve higher channel capacity, constituting the MIMO-OFDM technology [3], [4], which has been applied in power line communication (PLC) systems specified in ITU-T G.9963 and HomePlug AV2 standards [5]. Despite its advantages, MIMO-OFDM based PLC systems suffer from unfavourable degradation caused by non-Gaussian and nonlinear impulsive noise (IN), which is caused by the switches of electrical devices or strong radio frequency ingress, is one of the most commonly seen non-Gaussian noises that bring detrimental impacts on PLC systems [6], [7].

The IN is a serious bottleneck of the OFDM PLC system performance. If the IN energy exceeds a certain threshold, it is very difficult to mitigate its impacts on all the contaminated sub-carriers [7]. To mitigate the IN, some conventional methods have been proposed. Some researches focus on the clipping and/or blanking method to produce nonlinear processors for receivers against the IN [8]. A multiple channel selection combining scheme to suppress the IN defined by the Gaussian mixture model is proposed in [9]. Pre-coding and frequency algebraic interpolation techniques are implemented to detect the positions of IN [10]. However, the impacts of IN with high intensity cannot be effectively eliminated by conventional methods through suppressing the power of IN or clipping/blanking the useful data, which might result in data loss and performance degradation.

The recently emerged theory of compressed sensing (CS) [11]–[15] can be introduced to recover the IN signal to overcome these conventional difficulties. Since the IN is naturally a sparse signal in the time domain, it is likely to be recovered based on CS. Nevertheless, the research on CS-based IN mitigation is inadequate yet, among which the sparse convex optimization (SCO) method [16] is to utilize the unused sub-carriers as measurement data. In our previous work [17], the classical CS-based greedy algorithm of sparsity adaptive matching pursuit (SAMP) [18] is adopted to eliminate IN. However, state-of-art CS based methods are only aimed at the single input single output (SISO) system, and the IN cancellation for the newly emerged MIMO PLC system is lack of research. There exists the inherent spatial correlation of the IN signals in the MIMO PLC system, which can be utilized using the extended theory of CS, i.e., the theory of structured CS (SCS) [19], to further improve the performance of conventional CS-based methods, especially when the intensity of the IN is fluctuating and its sparsity is large.

As an emerging and breakthrough theory of sparse approximation, the SCS theory has drawn plenty of attention for the high recovery accuracy in sparse approximation and robustness to large sparsity levels [19]. However, to the best of the authors' knowledge, there is no related research on the IN mitigation based on the SCS theory for MIMO-OFDM

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systems. To fill this gap and improve the robustness and accuracy of state-of-arts, a novel SCS-based IN recovery scheme for MIMO-OFDM PLC systems is proposed in this paper, making full use of the spatial correlation of the IN in different receive antennas. The contributions are twofold:

- The SCS theory is introduced to the area of IN recovery for the first time, to derive the proposed method of spatially multiple measuring (SMM) and formulate the SCS convex optimization framework, fully exploiting the inherent spatial correlation of IN in MIMO PLC systems.
- The classical CS-based SAMP algorithm is improved and an enhanced SCS-based greedy algorithm, structured *a priori* aided SAMP (SPA-SAMP), is proposed, capable of recovering the IN with higher accuracy and robustness.

The rest of this paper is organized as follows: the models of the IN and the signal in the MIMO PLC system are described in Section II. Section III presents the proposed SCS-based formulation through the SMM method, and the SPA-SAMP algorithm for the IN reconstruction in MIMO-OFDM systems, constituting the main contribution of the paper. Simulation results are reported in Section IV to validate the proposed approach, followed by the conclusions.

$Notation$: Matrices and column vectors are denoted by boldface letters; $(\cdot)^{\dagger}$ and $(\cdot)^{H}$ denote the pseudo-inversion operation and conjugate transpose; $\|\cdot\|_r$ represents the ℓ_r-norm operation; $|\Pi|$ denotes the cardinality of the set Π; $\mathbf{v}|_{\Pi}$ denotes the entries of the vector $\mathbf{v}$ in the set of Π; $\mathbf{A}_{\Pi}$ represents the sub-matrix comprised of the Π columns of the matrix $\mathbf{A}$; $(\mathbf{A})_{i,j}$ denotes the entry at the i-th row and j-th column of matrix $\mathbf{A}$; Π^c denotes the complementary set of Π; $\max(\mathbf{v}, T)$ denotes the indices of the T largest entries of the vector $\mathbf{v}$.

II. System Model

A. Statistical Model of IN

The IN vector corresponding to the i-th OFDM symbol is denoted by $\boldsymbol{\xi}_i = [\xi_{i,0}, \xi_{i,1}, \cdots, \xi_{i,N-1}]^T$ of length N. One of the fundamental features of IN is that the IN vector is sparse, with the support $\Pi = \{j\,|\xi_{i,j} \neq 0\,,\ j = 0, 1, \cdots, N-1\}$ and sparsity level $K = |\Pi|$. The interference-to-noise ratio (INR) γ of the IN is represented by $\gamma = \mathbb{E}\{P\}/\sigma^2$, where $P = \sum_{j\in\Pi} |\xi_{i,j}|^2/K$ is the IN average power and σ^2 is the variance of additive white Gaussian noise (AWGN). The statistical properties of the instantaneous amplitude and the random occurrences of the IN have been empirically modeled in literature, mainly including the Gaussian mixture model [20] and the Middleton's Class A model [21].

The instantaneous amplitude of the time-domain asynchronous impulsive noise can be modeled by the Gaussian mixture distribution [20], with the probability density function (pdf) given by

$$p_Z(z) = \sum\nolimits_{j=0}^{J_m} \beta_j \cdot g_j(z), \tag{1}$$

where $g_j(z)$ is the pdf of Gaussian distribution with zero mean and variance of σ_j^2, β_j is the mixture coefficient of the corresponding Gaussian pdf, and J_m is the number of Gaussian components.

The Middleton's Class A model is a common statistical model of the IN with the parameters of the overlapping factor A and the background-to-impulsive-noise power ratio ω [21]. Gaussian mixture distribution can generate the special case of Middleton's Class A distribution when the parameters $\beta_j = e^{-A}A^j/j!$ and $\sigma_j^2 = (j/A + \omega)/(1+\omega)$ as $J_m \to \infty$.

The arrival rate of the IN bursts, i.e., the number of the IN bursts per second, follows Poisson process, and is given by the probability

$$P(\Lambda) = \lambda^{\Lambda} e^{-\lambda}/\Lambda!, \tag{2}$$

where λ denotes the rate of IN arrivals [22]. The Gaussian mixture model and the Poisson arrival process are adopted in this paper.

The IN also has an important characteristic among different receivers in the MIMO system, the spatial correlation, because the IN occurs in a burst manner in the time domain, and it will simultaneously have an impact on different receive antennas in the MIMO system. Since the spatial scale of receive antennas are small enough, the IN impacts on each of them take place at the same time samples. Hence, the spatial correlation indicates that the supports (the positions of the nonzero entries) of the IN signals at different receive antennas are the same, i.e. $\Pi^{(1)} = \Pi^{(2)} = \cdots = \Pi^{(N_r)} = \Pi$, although their amplitudes might be different from each other due to different channel conditions of different antennas.

B. MIMO-OFDM based PLC Signal Model

The signal frame and the frequency-domain structure of a typical MIMO-OFDM based PLC system specified in the ITU-T G.9963 PLC standard [5] are shown in Fig. 1. Without loss of generality, the 2×2 MIMO system configured in [5] is investigated in this paper, while the proposed scheme is also applicable in arbitrary $N_t \times N_r$ MIMO systems, where N_t and N_r are the number of transmit and receive antennas. The null sub-carriers, including the reserved tones and the virtual sub-carrier masks specified in PLC standards, are utilized by the proposed SMM method to acquire the measurement matrix for SCS based IN recovery. In the time domain, the i-th frame

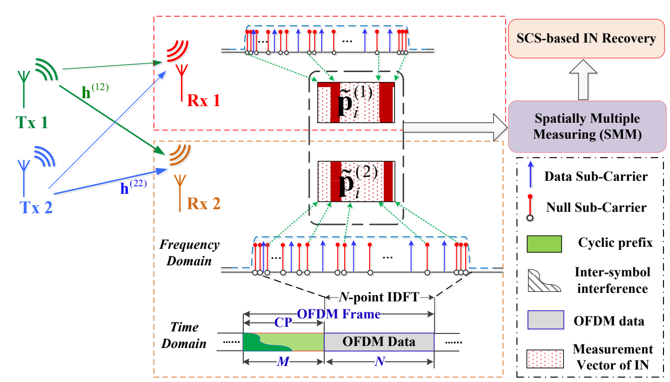

Fig. 1. Time-frequency OFDM frame structure exploited by the SMM method for the SCS-based IN recovery and cancellation.

consists of the OFDM symbol $\mathbf{x}_i = \left[x_{i,0}, x_{i,1}, \cdots, x_{i,N-1}\right]^T$ of length N and its cyclic prefix (CP). The i-th time-domain OFDM symbol $\mathbf{x}_i$ is the inverse discrete Fourier transform (IDFT) of the corresponding frequency-domain data in the N sub-carriers, which contains some reserved null sub-carriers whose indices are denoted by the set Ω. All the N_t transmit antennas are sending the OFDM symbols simultaneously, then passing through the PLC MIMO channel with the channel impulsive response (CIR) $\mathbf{h}^{(tr)} = \left[h_0^{(tr)}, h_1^{(tr)}, \cdots, h_{L-1}^{(tr)}\right]^T$ between the t-th transmit antenna and the r-th receive antenna. At the receiver, the received data at the r-th receive antenna in the null sub-carriers set Ω are denoted by

$$\tilde{\mathbf{p}}_i^{(r)} = \mathbf{F}_R \boldsymbol{\xi}_i^{(r)} + \tilde{\mathbf{w}}_i^{(r)}, \tag{3}$$

where the vector $\tilde{\mathbf{p}}_i^{(r)} = [\tilde{p}_{i,0}^{(r)}, \tilde{p}_{i,1}^{(r)}, \cdots, \tilde{p}_{i,R-1}^{(r)}]^T$ of length $R = |\Omega|$ is the measurement vector of the IN at the null sub-carriers, $\tilde{\mathbf{w}}_i^{(r)}$ denotes the corresponding frequency-domain AWGN vector, while the observation matrix utilized for SCS-based IN recovery is the partial DFT matrix $\mathbf{F}_R$ given by

$$\mathbf{F}_R = \frac{1}{\sqrt{N}}[\boldsymbol{\chi}_0 \quad \boldsymbol{\chi}_1 \quad \cdots \quad \boldsymbol{\chi}_{N-1}], \tag{4}$$

where the k-th entry of $\boldsymbol{\chi}_m$ is $\exp(-j2\pi mk/N), k \in \Omega, m = 0, \cdots, N-1$. Note that the measurement vector $\tilde{\mathbf{p}}_i^{(r)}$ at the set Ω only contains the components of IN and AWGN, while the information data component is not included since the null sub-carriers are set to zeros.

III. Structured Compressed Sensing Formulation and Algorithm for IN Recovery

A. Existing CS-based Measurements of IN for SISO systems

According to the classical CS theory, it is feasible to recover the IN signal $\boldsymbol{\xi}_i$ for the SISO system using the measurement vector $\tilde{\mathbf{p}}_i^{(r)}$ given by (3) in the presence of background AWGN $\tilde{\mathbf{w}}_i$ [12]. To solve the CS measurement model in (3), one can equivalently relax it to a convex ℓ_1-norm minimization problem, which can be efficiently solved by state-of-art CS-based greedy algorithms, such as SAMP [18] and PA-SAMP [17], [23]. However, these CS based methods are only aimed at the SISO system and ignores the spatial correlation of the IN in the MIMO system, which might result in performance degradation, particularly when the intensity of the IN is fluctuating and its sparsity is large.

B. Proposed SCS Formulation for IN Recovery in MIMO-OFDM System: Spatially Multiple Measuring of IN

To further improve the immunity to bad conditions, the SCS theory is introduced to extend our previous work [17] to MIMO-OFDM systems, leading to the proposed SMM method. In the $N_t \times N_r$ MIMO-OFDM system, the proposed SMM method exploits all the N_r measurement vectors given in (3) corresponding to the spatially correlated N_r receive antennas, yielding the SCS measurement model

$$\tilde{\mathbf{P}} = \left[\tilde{\mathbf{p}}_i^{(1)}, \tilde{\mathbf{p}}_i^{(2)}, \cdots, \tilde{\mathbf{p}}_i^{(N_r)}\right]_{R\times N_r} = \mathbf{F}_R \boldsymbol{\Xi} + \tilde{\mathbf{W}}, \tag{5}$$

where $\boldsymbol{\Xi} = [\boldsymbol{\xi}_i^{(1)}, \boldsymbol{\xi}_i^{(2)}, \cdots, \boldsymbol{\xi}_i^{(N_r)}]_{N\times N_r}$ is the spatially jointly sparse IN matrix whose columns share the same support Π due to the spatial correlation described in Section II-A, though the amplitudes of the nonzero values in the same row can be different for different receive antennas. $\tilde{\mathbf{W}} = [\tilde{\mathbf{w}}_i^{(1)}, \tilde{\mathbf{w}}_i^{(2)}, \cdots, \tilde{\mathbf{w}}_i^{(N_r)}]$ is the AWGN matrix.

The formulated mathematical model in (5) complies with the newly developed theory of SCS precisely [19], [24]. Each column of the measurements matrix $\tilde{\mathbf{P}}$ is one measurement vector of the IN related with one receive antenna, and the spatial correlation is taken good advantage of by the SCS measurements model. Afterwards, the multiple IN signals within $\boldsymbol{\Xi}$ that are jointly sparse can be simultaneously recovered by solving the nonlinear SCS optimization problem formulated as follows

$$\hat{\boldsymbol{\Xi}} = \arg \min_{\boldsymbol{\Xi}\in\mathbb{C}^{N\times N_r}} \|\boldsymbol{\Xi}\|_{0,q}, \text{s.t.} \left\|\tilde{\mathbf{P}} - \mathbf{F}_R\boldsymbol{\Xi}\right\|_{q,q} \le \varepsilon_S, \tag{6}$$

where ε_S denotes the bound of the constraint in (6) due to the AWGN noise $\tilde{\mathbf{W}}$, and $\ell_{p,q}$-norm of the matrix $\boldsymbol{\Xi}$ is defined by

$$\|\boldsymbol{\Xi}\|_{p,q} = \left(\sum_m \left\|(\boldsymbol{\Xi}^T)_m\right\|_q^p\right)^{1/p} \tag{7}$$

with $(\boldsymbol{\Xi}^T)_m$ being the m-th row of $\boldsymbol{\Xi}$. The SCS problem in (6) is a non-convex and NP-hard one since the $\ell_{0,2}$-norm is adopted [19]. Fortunately, it can be relaxed to a convex optimization problem by adopting the mixed $\ell_{1,2}$-norm [19], yielding

$$\hat{\boldsymbol{\Xi}} = \arg \min_{\boldsymbol{\Xi}\in\mathbb{C}^{N\times N_r}} \|\boldsymbol{\Xi}\|_{1,2}, \text{s.t.} \left\|\tilde{\mathbf{P}} - \mathbf{F}_R\boldsymbol{\Xi}\right\|_{2,2} \le \varepsilon_S, \tag{8}$$

where the error bound due to AWGN can be calculated by $\varepsilon_S = \sqrt{RN_r\sigma^2}$ accordingly. Note that the previously described CS-based approach can be regarded as a special case of the proposed SCS-based framework with $N_r = 1$ in (5) and (6). The SCS convex optimization problem (6) can be efficiently solved using the SCS-based greedy algorithms, such as simultaneous orthogonal matching pursuit (S-OMP) [25]. However, S-OMP requires the sparsity level to be known to reconstruct the sparse signal, which is impractical for the NBI signal in realistic PLC systems. Moreover, there is no *a priori* information exploited in state-of-art methods. Hence, we propose the SCS-based greedy algorithm of SPA-SAMP to solve the mixed $\ell_{1,2}$-norm minimization problem and improve the performance against conventional algorithms.

C. Enhanced SCS-based Greedy Algorithm for IN Recovery: Structured a Priori Aided Sparsity Adaptive Matching Pursuit

Unlike our previously proposed classical CS based greedy algorithm [17] which copes with only one-dimensional measurement vector, and thus is not robust in severe conditions, the proposed SCS-based greedy algorithm SPA-SAMP further improves the performance by exploiting the spatial correlation of the IN signals at multiple receive antennas to maximize the accuracy of each iteration in the greedy pursuit process.

Firstly, since the intensity of IN is normally much higher than that of data component or AWGN in the time domain, it is feasible to obtain a coarse *a priori* estimation of the partial support $\Pi^{(0)}$ of the IN signals at all the N_r receive antennas through thresholding. The indices of the time-domain samples in the i-th OFDM symbols $\{\mathbf{x}_i^{(r)}\}_{r=1}^{N_r}$ with the average power exceeding the given threshold λ_t are included in the partial support $\Pi^{(0)}$, which is given by

$$\Pi^{(0)} = \left\{ n \left| \frac{1}{N_r} \sum_{r=1}^{N_r} \left| x_{i,n}^{(r)} \right|^2 > \lambda_t, n = 0, 1, \cdots, N-1 \right. \right\}, \quad (9)$$

where the power threshold λ_t is given by

$$\lambda_t = \frac{\alpha}{N N_r} \sum_{r=1}^{N_r} \sum_{n=0}^{N-1} \left| x_{i,n}^{(r)} \right|^2, \quad (10)$$

where α is a coefficient that can be configured large enough to ensure the accuracy of the time-domain partial support of the IN. Afterwards, the *a priori* partial support estimation $\Pi^{(0)}$ can be exploited to facilitate the initialization and iterations of SPA-SAMP.

The SPA-SAMP algorithm is based on the relaxed convex SCS optimization problem in (8) by minimizing the $\ell_{1,2}$-norm of the IN spatially joint sparse matrix Ξ. Its pseudo-code is summarized in **Algorithm 1**. Specifically, the input includes the measurements matrix $\tilde{\mathbf{P}}$, the observation matrix $\boldsymbol{\Psi} = \mathbf{F}_R$, and the *a priori* partial support $\Pi^{(0)}$, as well as the iteration step size Δs, which can be a compromise between the convergence rate and the accuracy. During the multiple iterations, the accuracy of the temporary support estimation Π_t is improved at each iteration, and the testing sparsity level T is increased by Δs when the stage switches. The output is the final support Π_F and the recovered IN jointly sparse matrix $\hat{\boldsymbol{\Xi}}$, s.t. $\hat{\boldsymbol{\Xi}}|_{\Pi_F} = \boldsymbol{\Psi}_{\Pi_F}^{\dagger} \tilde{\mathbf{P}}, \hat{\boldsymbol{\Xi}}|_{\Pi_F^c} = \mathbf{0}$.

Afterwards, the r-th column of the recovered IN jointly sparse matrix $\hat{\boldsymbol{\Xi}}$ at the output of **Algorithm 1**, namely $\hat{\boldsymbol{\xi}}_i^{(r)}$, is exactly the estimated time-domain IN signal corresponding to the i-th OFDM symbol at the r-th receive antenna. Then, this recovered IN signal can be cancelled out from the received OFDM symbol before the following demapping and decoding.

IV. Simulation Results and Discussions

The performance of the proposed SCS-based SMM method with the SPA-SAMP algorithm for IN recovery and cancellation in the MIMO PLC systems is evaluated through simulations. Typically, the simulation setup is configured according to the G.9963 MIMO PLC standard [5]. The OFDM sub-carrier number $N = 1024$ and the number of null sub-carriers $R = 128$. The modulation scheme of 16QAM and the low density parity check (LDPC) code with code length of 8640 bits and code rate of 0.5 as specified in [5] are adopted. The 2×2 MIMO PLC multi-path channel [26] in the presence of IN is adopted, where $N_t = N_r = 2$. The coefficient for the partial support acquisition is $\alpha = 5.0$. The Gaussian mixture model of the IN is adopted with the parameters configured as $A = 0.15, \omega = 0.02, K = 10, \lambda = 50/\mathrm{sec}$ and γ=30 dB.

Algorithm 1 (*SPA-SAMP*): Structured *a Priori* Aided Sparsity Adaptive Matching Pursuit for NBI Recovery

Input:

1) The *a priori* estimated support $\Pi^{(0)}$
2) Initial sparsity level $K^{(0)} = |\Pi^{(0)}|$
2) Measurements matrix $\tilde{\mathbf{P}}$
3) Observation matrix $\boldsymbol{\Psi} = \mathbf{F}_R$
4) Step size Δs.

Initialization:

$\hat{\boldsymbol{\Xi}}^{(0)}\Big|_{\Pi^{(0)}} \leftarrow \boldsymbol{\Psi}_{\Pi^{(0)}}^{\dagger} \tilde{\mathbf{P}}$ (initially estimated IN matrix)
$\mathbf{R}^{(0)} \leftarrow \tilde{\mathbf{P}} - \boldsymbol{\Psi} \hat{\boldsymbol{\Xi}}^{(0)}$ (initial residue matrix)
$T \leftarrow K^{(0)} + \Delta s$ (initial testing sparsity level); $k \leftarrow 1$

Iterations:

repeat
  $\mathbf{v} \in \mathbb{C}^N$ s.t. $v_i = \sum_{j=1}^{N_r} \left| \left(\boldsymbol{\Psi}^H \mathbf{R}^{(k-1)} \right)_{i,j} \right|$
  $S_k \leftarrow \mathrm{Max}\{\mathbf{v}, T - K^{(0)}\}$ {Preliminary test}
  $L_k \leftarrow \Pi^{(k-1)} \cup S_k$ {Make candidate list}
  $\mathbf{u} \in \mathbb{C}^{|L_k|}$ s.t. $u_i = \sum_{j=1}^{N_r} \left| \left(\boldsymbol{\Psi}_{L_k}^{\dagger} \tilde{\mathbf{P}} \right)_{i,j} \right|$
  $\Pi_t \leftarrow \mathrm{Max}\{\mathbf{u}, T\}$ {Temporary final list}
  $\hat{\boldsymbol{\Xi}}^{(k)}\Big|_{\Pi_t} \leftarrow \boldsymbol{\Psi}_{\Pi_t}^{\dagger} \tilde{\mathbf{P}}$; $\hat{\boldsymbol{\Xi}}^{(k)}\Big|_{\Pi_t^c} \leftarrow \mathbf{0}$
  $\mathbf{R} \leftarrow \tilde{\mathbf{P}} - \boldsymbol{\Psi}_{\Pi_t} \boldsymbol{\Psi}_{\Pi_t}^{\dagger} \tilde{\mathbf{P}}$ {Compute residue}
  if $\|\mathbf{R}\|_{2,2} \geq \left\| \mathbf{R}^{(k-1)} \right\|_{2,2}$ **then**
    $T \leftarrow T + \Delta s$ {Stage switching}
  else
    $\Pi^{(k)} \leftarrow \Pi_t$; $\Pi_F \leftarrow \Pi_t$; $\mathbf{R}^{(k)} \leftarrow \mathbf{R}$
    $k \leftarrow k + 1$ {Same stage, next iteration}
  end if
until $\|\mathbf{R}\|_{2,2} \leq \varepsilon_S$

Output:

1) Final support Π_F
2) Recovered jointly sparse IN matrix $\hat{\boldsymbol{\Xi}}$, s.t. $\hat{\boldsymbol{\Xi}}\Big|_{\Pi_F} = \boldsymbol{\Psi}_{\Pi_F}^{\dagger} \tilde{\mathbf{P}}, \quad \hat{\boldsymbol{\Xi}}\Big|_{\Pi_F^c} = \mathbf{0}$

The performance of one realization of the IN recovery using the proposed SCS-based SMM method with the SPA-SAMP algorithm for the 2×2 MIMO PLC system is depicted in Fig. 2. The partial support is firstly obtained using the threshold λ_t in (10). From the null sub-carriers sets at the N_r receive antennas, we can get the measurements matrix from which the accurate IN is recovered using SPA-SAMP. It is observed from Fig. 2 that the final IN estimation matches the actual IN very well.

The mean square error (MSE) performances of the proposed SMM method with the SCS-based SPA-SAMP algorithm, and the state-of-art CS-based algorithms (PA-SAMP [17] and SAMP [18]) for IN recovery in the 2×2 MIMO PLC system are shown in Fig. 3. The theoretical Cramer-Rao lower bound (CRLB) $2\sigma^2 \cdot (N \cdot K/R)$ [27] is illustrated as benchmark. It can be observed that the proposed SCS-based SPA-SAMP algorithm achieves the MSE of 10^{-3} at the INR of 23.2 dB and 32.0 dB with $K = 8$ and $K = 16$, respectively, which

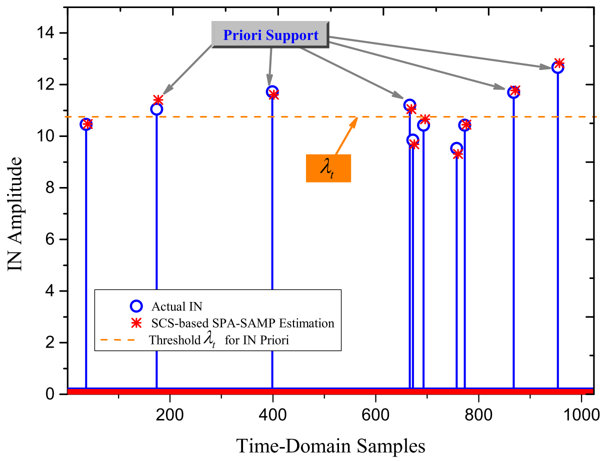

Fig. 2. Graphical visualization of the IN recovery using the proposed SCS-based SMM method with the SPA-SAMP algorithm.

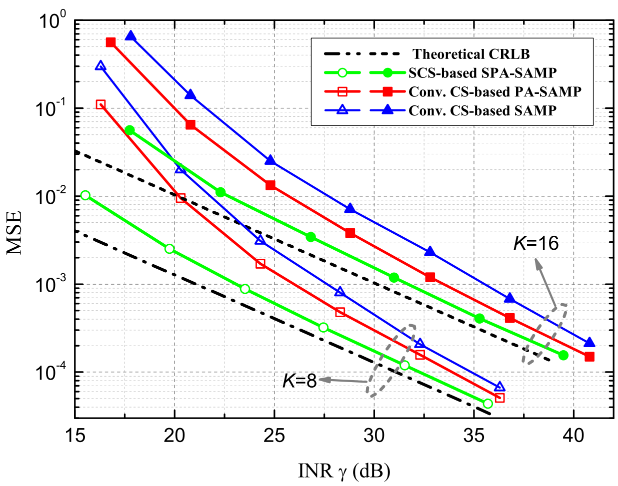

Fig. 3. MSE performance of the IN reconstruction using the proposed SCS-based SMM method with the SPA-SAMP algorithm compared with state-of-art CS-based methods in the 2×2 MIMO PLC system.

outperforms conventional PA-SAMP and SAMP algorithms by approximately 2.2 dB and 3.8 dB, respectively. It is noted from Fig. 3 that the MSE of the proposed SPA-SAMP is asymptotically approaching the theoretical CRLB with the increase of the INR, verifying the high recovery accuracy. Moreover, the introduction of SCS will reduce the required length of measurement vector from $\mathcal{O}(K\log_2(N/K))$ in the standard CS downto $\mathcal{O}(K)$ in SCS [28], leading to slacker measurement requirement and higher spectral efficiency.

The BER performances of different IN mitigation and cancellation schemes in the 2×2 MIMO PLC system are illustrated in Fig. 4, including the proposed SCS-based SMM method with the SPA-SAMP algorithm, as well as the conventional non-CS-based method (clipping and blanking [8]), and the state-of-art CS-based methods (SCO [16] and our previously proposed PA-SAMP [17]). The worst case ignoring IN, and the ideal case without IN are also depicted as benchmarks. It can be found that at the target BER of 10^{-4}, the proposed SCS-

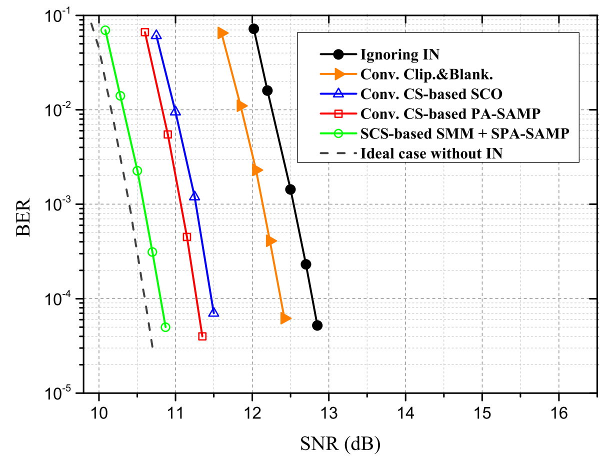

Fig. 4. BER performance of different schemes for IN mitigation and cancellation for the 2×2 MIMO PLC system.

based scheme outperforms the conventional CS-bsed methods (SCO and PA-SAMP), the conventional non-CS-based method (clipping and blanking), and the case ignoring IN by approximately 0.7 dB, 1.6 dB, and 2.1 dB, respectively. Furthermore, the gap between the proposed method and the ideal case without IN is only about 0.2 dB, validating the accuracy and effectiveness of the proposed IN recovery scheme.

V. Conclusion

A novel SCS-based scheme of IN cancellation for MIMO PLC systems is proposed in this paper. The lack of research on the IN mitigation for MIMO PLC systems is changed by the proposed spatially multiple measuring method along with the enhanced SCS-based greedy algorithm SPA-SAMP, which introduced the powerful emerging SCS theory into the area of IN mitigation for the first time. The spatial correlation of the IN signals at different receive antennas are fully exploited, leading to the measurements matrix and the formulation of the SCS convex optimization model. The IN signal is then reconstructed by the proposed SCS-based greedy algorithm SPA-SAMP, which is specifically designed and improved for the MIMO PLC system. Furthermore, the proposed scheme is applicable and can be easily extended to other MIMO-OFDM based broadband transmission systems in the presence of IN.

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