

Rebuttals to Reviews: Boundary Multiple Measurement Vectors for Multi-Coset Sampler

Dong Xiao, Jian Wang and Yun Lin

We provide a new experiment that compares the recent algorithm DTMP in the literature [16] with SI-SSP. The high sparsity case which has been studied in many compressed sensing literature absolutely can be still valid for SI-SSP and details can be seen in Fig. 1. In our experiments, we consider a multi-band signal with frequency range $[-5, 5]$ GHz and $N_{\text{sig}} = 3$ PU's signals, whose bandwidths are $B = 100$ and 500 MHz corresponding to $\frac{L}{M} = 2$ and 6 , respectively. We divide the frequency range into $L = 100$ cosets and use $p \in [6, 20]$ channels or $p \in [36, 50]$ channels to get the MCS signals, with delay coefficients randomly generated. We set conditions where $\frac{L}{M} = 6$, $N_{\text{sig}} = 3$ and the $|\text{supp}(\mathbf{X})| = 18$. The sparsity of \mathbf{X} is a very high value for the signal length $L = 100$.

Moreover, we add Gaussian white noise to the signal with signal-to-noise ratio (SNR) of $\{-10, 10, 30\}$ dB. In bMMV, we consider $r = 4$ partitioning sub-matrices and set $\omega = 0.8$ to the weighting matrix \mathbf{W} . In SI-SSP, we select triple noise variance as the tolerance. In DTMP, we select the hyper-parameter constant $C = \{3, 0.001, 0.001\}$ for $\text{SNR} = \{-10, 10, 30\}$. To compare the recovery accuracy of SI-SSP with DTMP, we use the detection probability P_d and false alarm probability P_f as metrics.

From Fig. 1, SI-SSP has a better recovery performance than DTMP algorithm in both the low and high signal sparsity cases.

We give the computational analysis of SI-SSP. First, in each iteration, the subsequent selection requires $O(pNL/r)$ computations for a sub-matrix in general. Second, in each iteration, the cost of computing the projections is of $O(pK^2N/r)$ the order for a sub-matrix where $K = |\text{supp}(\mathbf{X})|$. Then, we could sum the two-part costs to get $O(pK^2N/r + pNL/r)$ computations. Finally, we consider that SI-SSP repeats $O(K)$ iterations and there r sub-matrices, the total time complexity of SI-SSP is upper-bounded by $O(pN(L + K^2))$. When the signal is very sparse, in particular, when $K^2 < O(L)$, the total complexity of SI-SSP is upper-bounded by $O(pNL)$.

The restricted isometry property (RIP) framework can be defined on the complex field. We have:

Definition 1. A sensing matrix $\mathbf{A} \in \mathbb{C}^{m \times n}$ is said to satisfy the s -order RIP if for any s -sparse ($\|\mathbf{x}\|_0 \leq s$) signal $\mathbf{x} \in \mathbb{C}^n$

$$(1 - \delta) \|\mathbf{x}\|_2^2 \leq \|\mathbf{Ax}\|_2^2 \leq (1 + \delta) \|\mathbf{x}\|_2^2, \quad (\text{S.1})$$

where $0 \leq \delta < 1$. The infimum of δ , denoted by δ_s , is called the restricted isometry constant (RIC) of \mathbf{A} .

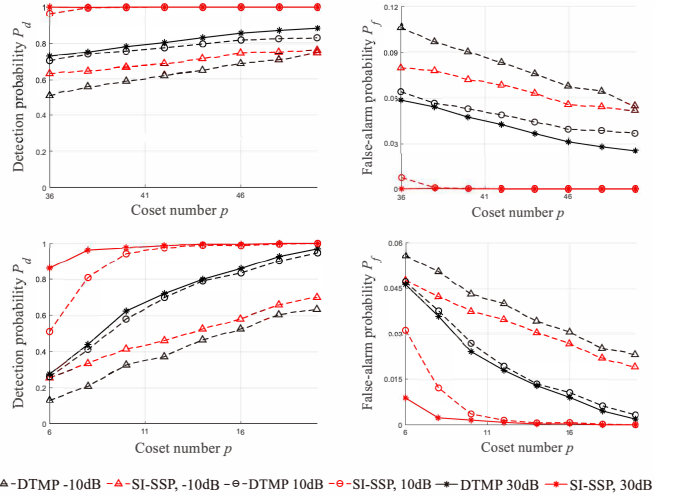


Fig. 1. P_d and P_f of DTMP and SI-SSP against p from 6 ~ 20 and 36 ~ 50 with $\text{SNR} = \{-10, 10, 30\}$ dB. From above to below: the signal with $\frac{L}{M} = 6$ is decomposed into $r = 4$ sub-matrices and the signal with $\frac{L}{M} = 2$ is decomposed into $r = 4$ sub-matrices.