SSPD Conference

Compressive Self-Noise Cancellation in Underwater Acoustics

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Contribution

- Purpose of sonar → detect the stealthy target in shallow water
- Main barrier in target detection → sonar's self-noise.
- Goal → Suppress the self-noise.
- Conventional subspace-based → high computationally complex.
- Proposed compressed sensing based methods for self-noise suppression.
- Proposed methods work for both narrowband and broadband targets at very low SINR.

Introduction

- Major problems in target detection → self-noise of sonar.
- Present near the ship → amplitude is more than target signal.
- Objective → self and ambient noise cancellation, so that targets can be detected.

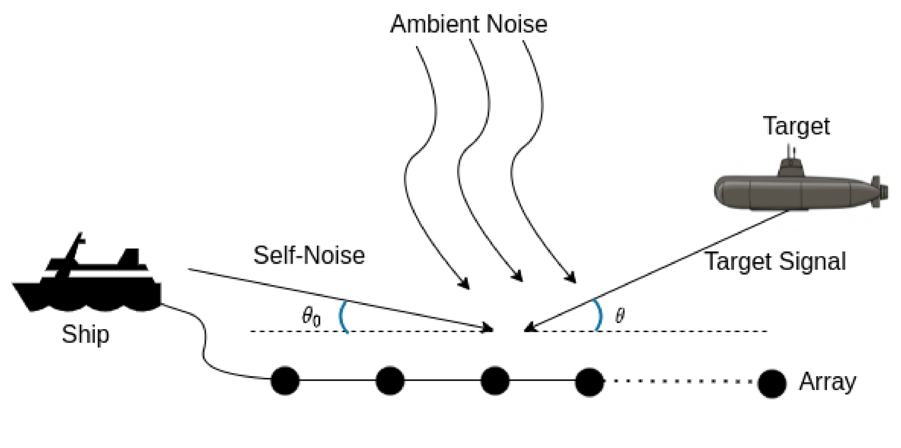

Figure 1: Signal Reception on Towed Array

Array Data Model

- Received signal on n^{th} sensor of ULA is:

$$\mathbf{y}[n] = \mathbf{A}(\theta)\mathbf{s}[n] + \mathbf{a}(\theta_0)s_o[n] + \mathbf{v}[n] \quad (1)$$

$\mathbf{s}[n]$ → signal vector, s_0 → self-noise, $\mathbf{v}[n]$ → additive Gaussian noise.

$\mathbf{A}(\theta)$ → the steering matrix for $\mathbf{s}[n]$, $\mathbf{a}(\theta_0)$ is steering vector for s_0

θ is direction of arrival (DOA) of signal, θ_0 is DOA for self-noise.

- Received noisy signal at ULA is

$$\mathbf{Y} = [[\mathbf{y}(1)], [\mathbf{y}(2)], [\mathbf{y}(3)], \cdots [\mathbf{y}(N)]] \quad (2)$$

- Signal model in matrix form: $\mathbf{Y} = \mathbf{S} + \mathbf{Z}$
- Goal → recover the signal component $\mathbf{S}$ by removing undesired component $\mathbf{Z}$.

Conventional Method

- Conventional method → null space projection.
- The optimal solution [3]:
$\hat{\mathbf{S}} = \mathbf{P}\mathbf{Y}$; $\mathbf{P} = (\mathbf{I} - \mathbf{U}\mathbf{U}^{\dagger})$
$\mathbf{P}$ → projection matrix, $\dagger$ → pseudo-inverse, $\mathbf{U}$ is sampled orthogonal vectors (SOV) using SVD or QR.

Proposed Method

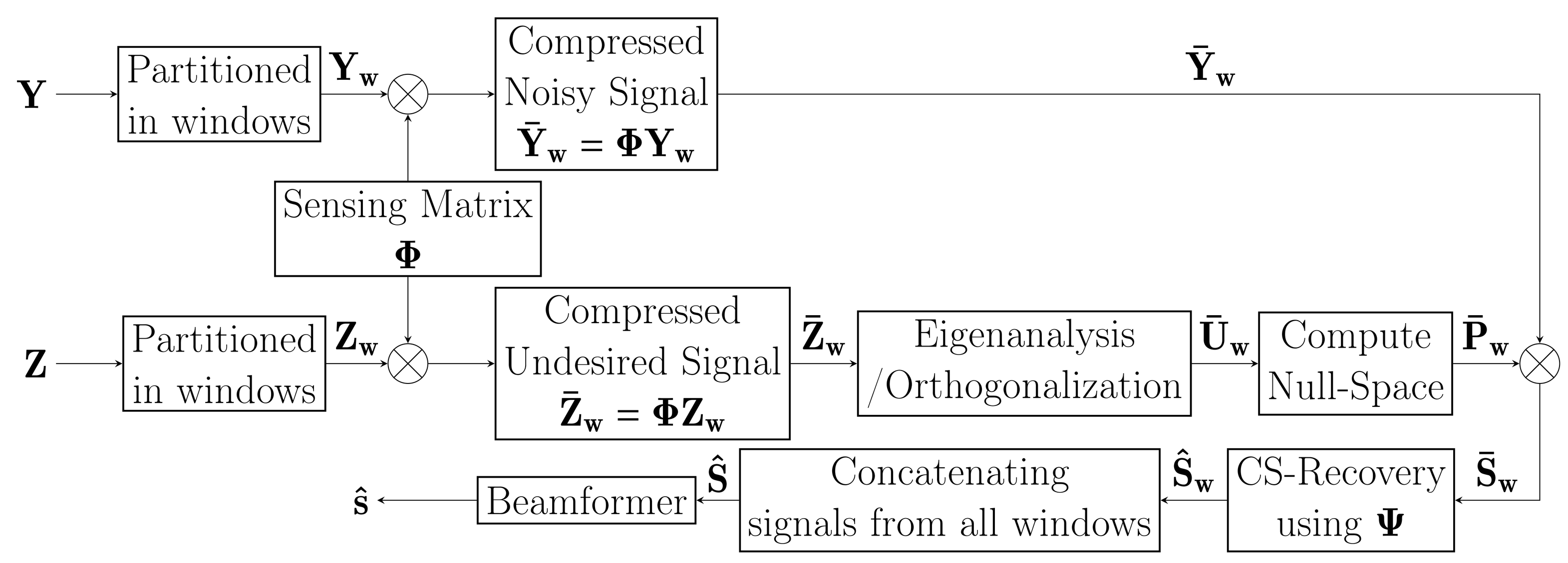

Figure 2: Compressive self-noise cancellation

- Utilizing null-space projection method in compressive domain [1, 2]

$$\bar{\mathbf{S}}_\mathbf{w} = \bar{\mathbf{P}}_\mathbf{w}\mathbf{\Phi}\mathbf{Y}_\mathbf{w};\ \bar{\mathbf{P}}_\mathbf{w} = (\mathbf{I} - \bar{\mathbf{U}}_\mathbf{w}\bar{\mathbf{U}}_\mathbf{w}^{\dagger}) \quad (3)$$

- $\mathbf{\Phi} \in \mathbb{R}^{l \times L} (l << L)$ → the sensing matrix consisting of 'l' random orthonormal vectors.
- Signal from each sensor → k-sparse (as columns of $\mathbf{A_w}$) in a basis $\mathbf{\Psi}$ [1].
- Estimation of the signal matrix → solve N independent inverse-problem:

$$\text{argmin}\|\bar{\mathbf{S}}_\mathbf{w} - \mathbf{\Phi}\mathbf{\Psi}\mathbf{A}_\mathbf{w}\|_F^2 \text{ s.t. } \|\mathbf{a}_i\|_0 \le k, \quad \mathbf{A}_w = [\mathbf{a}_1 \quad \mathbf{a}_2 \quad \mathbf{a}_3 \quad \ldots]; \quad \hat{\mathbf{S}}_\mathbf{w} = \mathbf{\Psi}\hat{\mathbf{A}}_\mathbf{w} \quad (4)$$

- Thus, the proposed method reduces time complexity to $\mathcal{O}(L^2N)$ as compared to the high-dimensional subspace-based method ($\mathcal{O}(l^2N)$).

Experimental Results : Beampattern

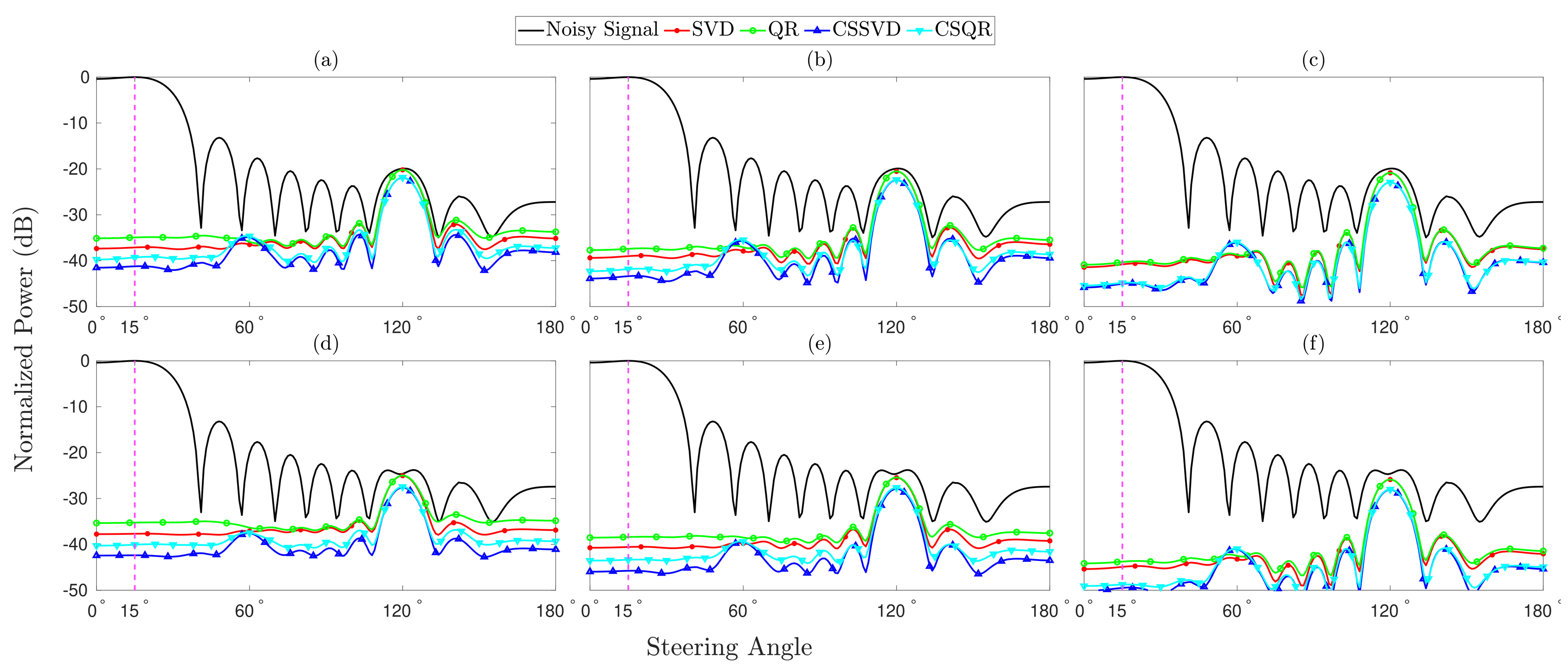

Figure 3: Beampattern for NB stationary signal at SINR (a,b,c) -20dB and (d,e,f) -25dB, (a,d) top 10, (b,e) top 20 and (c,f) top 30 SOV

Waterfall dispaly

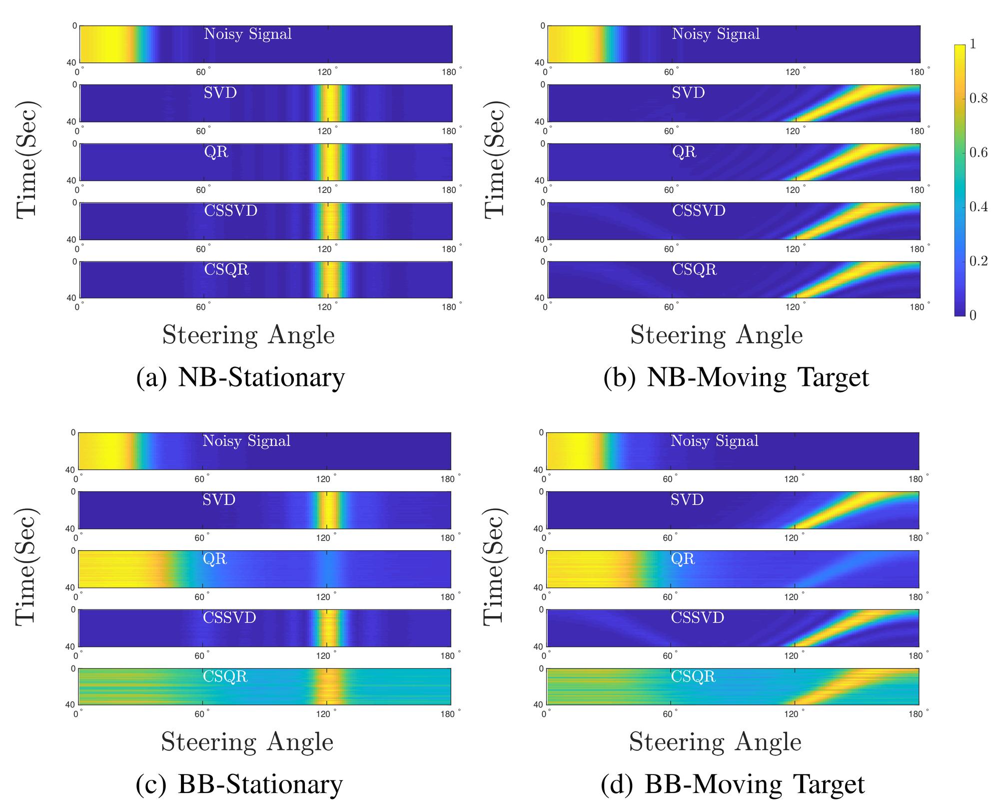

Figure 4: Waterfall Display at SINR -20 dB, top 20 SOV

SN-PLR (TPL) at -25 dB

SOV	SVD	QR	CSSVD	CSQR
10	37.69 (5.10)	35.26 (**5.05**)	**42.38** (7.68)	40.07 (7.52)
20	40.58 (5.53)	38.40 (**5.48**)	**45.76** (7.69)	43.35 (7.71)
30	44.91 (5.94)	43.77 (**5.92**)	**49.49** (8.16)	48.77 (8.09)

Conclusions

- Novelty → combination of the subspace-based. noise-cancellation approach with CS-based target localization in the presence of self and ambient noise.
- Low computational complexity than null-space projection method.
- Future work → optimizing the sensing matrix for multiple target localization.

References

[1] Richard G. Baraniuk, "Compressive sensing," *IEEE Signal Processing Magazine*, vol. 24, no. 4, pp. 118 – 121, 2007.

[2] Emmanuel J. Candes, Michael B. Wakin, and Stephen P. Boyd, "Enhancing sparsity by reweighted ℓ1 minimization," *Journal of Fourier Analysis and Applications*, vol. 14, no. 5, pp. 877–905, 2008.

[3] M Remadevi, N Sureshkumar, R Rajesh, and T Santhanakrishnan, "Cancellation of towing ship interference in passive sonar in a shallow ocean environment," *Defence Science Journal*, vol. 72, no. 1, pp. 122–132, 2022.