2025 Asia Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)

A Sliding-Window Range–Bearing Scan STAP for Underwater Active Sonar Target Detection

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***Abstract*—This paper presents a Sliding-Window Range–Bearing Scan STAP (SWRB-STAP) method for underwater active sonar target detection. First, the fast-time data are partitioned into fine-range cells, and at each cell a local covariance estimate is obtained via a guard/training sliding-window strategy to precisely suppress reverberation at different ranges. Next, narrowband STAP filtering is performed in parallel across all range cells and bearing angles to generate a two-dimensional range–bearing power map. Semi-physical/synthetic results demonstrate that SWRB-STAP can significantly suppress clutter and reliably detect weak targets in reverberant environments.**

I. INTRODUCTION

The vastness of the ocean presents significant challenges for active sonar operations, as reverberation—beyond vessel noise and ambient ocean noise—constitutes a primary interference affecting detection performance. Reverberation is generated when the transmitted signal is scattered by inhomogeneous media or irregular boundaries in the water, producing numerous scattered waves that coherently combine at the receiving transducer array. Effective suppression of reverberation is essential; otherwise, sonar performance degrades severely.

Reverberation is a special interference intrinsically linked to the transmitted pulse, and its spectral and angular coverage largely overlap those of the transmit signal. Under such conditions, cascaded spatial and temporal filtering suffers substantial performance loss in reverberation suppression and target detection. However, when a target has nonzero radial velocity relative to the array, its echo and the reverberation become separable in the angle–Doppler domain. Exploiting this characteristic, space–time adaptive processing (STAP) extends conventional temporal or spatial filtering to a two-dimensional joint filter in both domains [1]. In recent years, sonar researchers worldwide have attempted to apply STAP to reverberation suppression, achieving notable progress [2]-[8]. Nevertheless, many STAP studies rely either on strong a priori assumptions about clutter statistics or on coarse range resolution, making weak targets at near or far ranges difficult to detect in realistic sea conditions.

In this paper, we propose a sliding-window range–bearing STAP method—termed Sliding-Window Range–Bearing Scan STAP (SWRB-STAP)—for underwater active sonar target detection. First, the fast-time samples are partitioned into multiple range cells, and a guard/training sliding-window strategy is used for local covariance estimation at each cell, enabling more accurate reverberation suppression across different ranges. Next, narrowband STAP is applied to each sliding-window range cell, and the beamformer output power is computed in parallel for all bearing angles within that cell, producing a two-dimensional range–bearing power map that achieves continuous reverberation suppression and target localization. Unlike conventional STAP—which processes the entire fast-time record in a single pass—SWRB-STAP performs independent covariance estimation and filtering at each micro range gate, allowing fine-grained modeling of clutter characteristics at different ranges. This approach enhances target detection accuracy and stability, and its effectiveness is validated using semi-physical/synthetic data.

The following is the structure: Section 1 provides an introduction; Section 2 details the principles of underwater narrowband STAP and the proposed SWRB-STAP method; Section 3 presents semi-physical/synthetic results and analysis; and Section 4 concludes the paper.

II. PRINCIPLE OF SWRB-STAP

This section first presents the fundamental principles of single-pulse STAP (Space–Time Adaptive Processing) for underwater active sonar and then provides a detailed description of the proposed Sliding-Window Range–Bearing Scan STAP (SWRB-STAP), including its core concepts and algorithmic procedure.

A. Principle of single-pulse STAP for Active Sonar

In single-pulse active sonar, each range cell contains $M = T \times f_s$ fast-time samples, N array elements receive space–time data across K range cells, yielding a $K \times NM$ dimensional space–time data block. Rearranging this block according to STAP conventions, the received data dimension for one dwell becomes $K \times N \times M$ -dimensional, and the signal received within a single range cell is a $N \times M$ -dimensional vector.

After data reordering, a space–time snapshot is constructed. Let $x_{n,k}^{m}$ denote the *mth* fast-time sample in the *kth* range cell received by the *mth* array element. In general, the data for the *kth* range cell can be written as $\boldsymbol{X}_k = \begin{bmatrix} \boldsymbol{x}_{k,0} & \boldsymbol{x}_{k,1} & \cdots & \boldsymbol{x}_{k,M-1} \end{bmatrix} \in \mathbb{C}^{N \times M}$. By stacking all $\boldsymbol{X}_k$, column-wise, we obtain one $NM \times 1$ -dimensional space–time snapshot:

$$\boldsymbol{\gamma}_k = \mathrm{vec}\left(\boldsymbol{X}_k\right) = \begin{bmatrix} \boldsymbol{x}_{k,0}^{\mathrm{T}} & \boldsymbol{x}_{k,1}^{\mathrm{T}} & \cdots & \boldsymbol{x}_{k,M-1}^{\mathrm{T}} \end{bmatrix}^{T} \tag{1}$$

Assume the active sonar receive array is an *N*-element uniform linear array with element spacing d of half a wavelength. The target is assumed to be in the far field, and reverberation is modeled as plane waves incident on the array from the horizontal plane at various bearing angles θ. The geometric relationship between the array and the target is illustrated in Fig. 1.

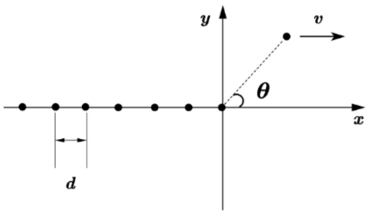

Fig. 1 Geometry between the array and the target.

The target normalized Doppler frequency is $v_d = \dfrac{f_d}{f_\mathrm{s}}$, the target normalized spatial frequency is $v_s = \dfrac{d}{\lambda}\cos\theta_i$, f_d denotes the reverberation's Doppler frequency, and λ is the transmit wavelength. The vector $\boldsymbol{S} \in \mathbb{C}^{MN \times 1}$ is called the target space–time steering vector which is given by:

$$\boldsymbol{S} = \boldsymbol{S}\left(v_d\right) \otimes \boldsymbol{S}\left(v_s\right) \triangleq \boldsymbol{S}\left(v_s, v_d\right) \tag{2}$$

$\otimes$ denotes the Kronecker product, and

$$\boldsymbol{S}\left(v_d\right) = \begin{bmatrix} 1 & \mathrm{e}^{\mathrm{j}2\pi v_d} & \cdots & \mathrm{e}^{\mathrm{j}2\pi(M-1)v_d} \end{bmatrix}^{\mathrm{T}} \in \mathbb{C}^{M \times 1} \tag{3}$$

$$\boldsymbol{S}\left(v_s\right) = \begin{bmatrix} 1 & \mathrm{e}^{-\mathrm{j}2\pi\sigma v_s} & \cdots & \mathrm{e}^{-\mathrm{j}2\pi(N-1)\sigma v_s} \end{bmatrix}^{\mathrm{T}} \in \mathbb{C}^{N \times 1} \tag{4}$$

are referred to as the temporal steering vector and spatial steering vector, respectively.

The goal of space–time joint processing is to solve for a weight coefficient $w_{n,k}^{m}$ corresponding to each space–time sample $x_{n,k}^{m}$, and then to weight and sum all space–time samples.

$$y_k = \sum_{n=1}^{N}\sum_{m=1}^{M} w_{n,k}^{m} x_{n,k}^{m} \tag{5}$$

The weight vector $\boldsymbol{w}$, composed of the coefficients $w_{n,k}^{m}$, is obtained via the linearly constrained minimum variance (LCMV) criterion. The LCMV criterion constrains the filter gain in the desired signal direction while minimizing the output power of the reverberation, it solves the following optimization problem:

$$\begin{cases} \min_{w} \boldsymbol{w}^{\mathrm{H}} \mathbf{R} \boldsymbol{w} \\ \text{s.t. } \boldsymbol{w}^{\mathrm{H}} \boldsymbol{S} = 1 \end{cases} \tag{6}$$

By applying the method of Lagrange multipliers to solve this optimization problem, we obtain:

$$\boldsymbol{w} = \frac{\boldsymbol{R}^{-1}\boldsymbol{S}}{\boldsymbol{S}^{\mathrm{H}}\boldsymbol{R}^{-1}\boldsymbol{S}} \tag{7}$$

The weight vector $\boldsymbol{w}$ given in (6) guarantees that y has the maximum output signal-to-clutter ratio; therefore, $\boldsymbol{w}$ is called the optimal weight vector, and the corresponding technique is referred to as optimal STAP. In practice, the reverberation covariance matrix $\boldsymbol{R}$ of the primary data is generally unknown and must be estimated from secondary data. The most common estimator is the maximum likelihood estimator (MLE), whose result is called the sample covariance matrix, denoted by $\boldsymbol{R}$, namely

$$\boldsymbol{R} = \frac{1}{k}\sum_{k=1}^{K} \gamma_k \gamma_k^{\mathrm{H}} \tag{8}$$

By substituting $\boldsymbol{R}$ from (8), the estimated weight vector becomes:

$$\boldsymbol{w} = \frac{\boldsymbol{R}^{-1}\boldsymbol{S}}{\boldsymbol{S}^{\mathrm{H}}\boldsymbol{R}^{-1}\boldsymbol{S}} \tag{9}$$

By substituting $\boldsymbol{w}$ into (5), the optimal STAP filtering is completed.

B. *SWRB-STAP*

To overcome the limitation of conventional STAP processing—which assumes uniform clutter characteristics across all ranges by processing the entire fast‑time record at once—this paper proposes the Sliding-Window Range–Bearing Scan STAP (SWRB-STAP). Its core idea is to partition the fast‑time samples into multiple small range cells and perform local covariance estimation and STAP filtering on each cell, thereby achieving precise, range‑dependent adaptation to varying clutter and reverberation. The main steps and underlying principles are as follows:

First, perform range‑cell partitioning. Based on the sound speed c and the transmit bandwidth B, compute the range resolution ΔR, and then determine the number of fast‑time samples corresponding to each range cell.

$$L = \left\lceil f_s \cdot \frac{2\Delta R}{c} \right\rceil \tag{10}$$

Thus, the 1 s of fast-time samples are divided into N_{cell} range cells, indexed by k=1, 2, … N_{cell} ,

$$N_{\text{cell}} = f_s / L \tag{11}$$

Each range cell contains N array elements and L fast-time samples, forming an (N×L) -dimensional space–time snapshot.

To prevent target signal leakage into the training set, a guard region is reserved on both sides of each test cell. Let the number of guard cells be G meaning that $G\times L$ samples on each side are skipped; let the number of training cells be P, so that beyond each guard region, P adjacent cells on the left and right are used as training.

Thus, for the *k-th* cell (where $k = G+P+1,\ldots,N_{\text{cell}}-G-P$), the training set consists of the snapshots from P cells on either side—skipping the G guard cells—so that there are *2P* training cells in total. As the window shifts one cell to the right, the training set is updated accordingly to capture the local reverberation variations. The set of training cell indices can be written as:

$$\boldsymbol{X}_{\text{train}} = \left[\boldsymbol{x}_{k-(G+P)},\ldots,\boldsymbol{x}_{k-(G+1)},\boldsymbol{x}_{k+(G+1)},\ldots,\boldsymbol{x}_{k+(G+P)}\right] \in \mathbb{C}^{(NL)\times(2P)} \tag{12}$$

Performing covariance estimation yields:

$$\boldsymbol{R} = \frac{1}{2P}\boldsymbol{X}_{\text{train}}\boldsymbol{X}_{\text{train}}^{H} \tag{13}$$

By subdividing the range into cells and performing local covariance re-estimation for each cell, more precise adaptive modeling of clutter and reverberation characteristics at different ranges is achieved. The output powers for all cells k across all bearing angles are assembled into a matrix $\left\{P_k\left(\theta_j\right)\right\} \in \mathbb{R}^{N_{\text{cell}}\times n_\theta}$, which is then plotted with range and bearing as the axes.

III. SIMULATION SETUP AND RESULT ANALYSIS

A. *Experimental Background (Using Semi-Physical/Synthetic Data)*

The test site was located in Qiandao Lake, where water depths typically range from 5 to 20 meters. Although surface waves are minimal under calm conditions, the complex bathymetry produces strong boundary reverberation. First, the required signal type and frequency were generated in MATLAB, and then the computer output was connected to a transducer and a power amplifier. Emission was carried out using a directional sound source (model: MEMS, developed by China State Shipbuilding Corporation) paired with an FL-1 transducer (Harbin Engineering University) and an L6 power amplifier (Ningbo Yongke). The source was submerged to a depth of 5 meters. The receive array was a 48-element horizontal array (developed by China State Shipbuilding Corporation), mounted on a trapezoidal frame and deployed to 5 meters depth via tethering. Hydrophones were spaced at 0.05 m intervals, giving the array a total aperture of 2.4 m.

Because the measured signal was an HFM waveform with Doppler‑invariant properties, time–frequency analysis via frequency shifts was infeasible. Therefore, a semi‑physical/synthetic approach was adopted: simulated target echoes were added to portions of the measured data dominated by reverberation, in order to validate the algorithm's effectiveness under real reverberant conditions.

The added simulated signal was an LFM waveform with amplitude 0.2 and the same frequency parameters as the transmit signal. The simulated target arrived from a bearing of 60°, with a radial velocity of 0.5 m/s relative to the array. Two target ranges—150 m and 200 m—were chosen within regions of strong reverberation. By comparing the matched‑filter beamforming outputs with the space–time filtered outputs after embedding the LFM echoes, the reliability of the SWRB-STAP space–time filtering method was preliminarily confirmed.

B. *Results and Analysis*

First, the entire time-series data from the received array were analyzed. From the experimental measurements, approximately 100 real-time bearing images were generated via matched-filter beamforming. One representative matched-filter beamforming image from the array's received data is shown in Fig. 2. Strong reverberation interference is observed in the 50-150 m range.

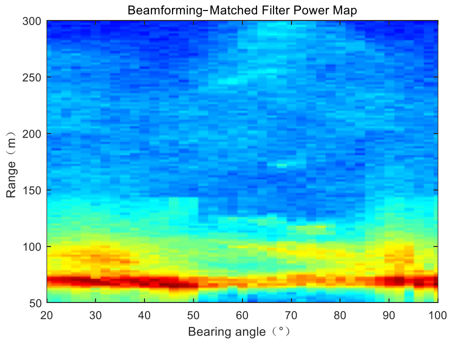

Fig2. Beamforming-matched filter power map of the array-received signal

Simulated echoes were added to the original element-domain received signal to construct semi-physical/synthetic data. The signal received by the first array element is shown in Fig. 3. By inserting a simulated echo at 100 m (within the strong reverberation zone) and another at 200 m and 60° bearing, the resulting semi-physical/synthetic signal with the target at 100 m is shown in Fig. 4, and semi-physical/synthetic signal with the target at 200 m is shown in Fig. 5.

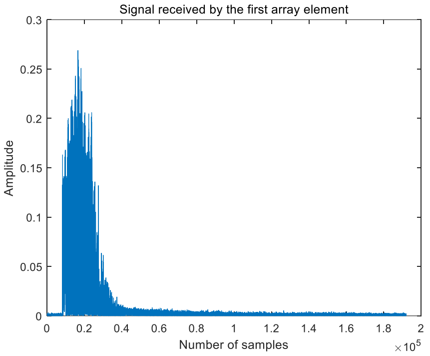

Fig 3. Signal received by the first array element

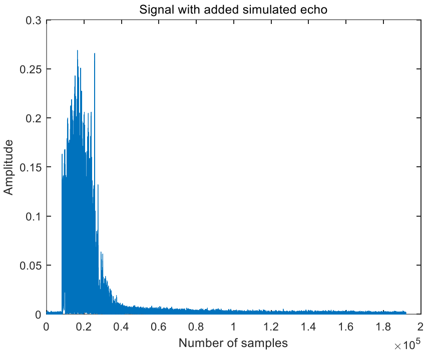

Fig 4. Semi-physical/synthetic signal with target at 100 m

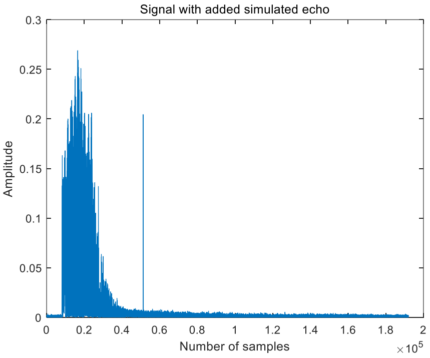

Fig 5. Semi-physical/synthetic signal with target at 200 m

Perform wideband beamforming followed by time-domain matched filtering, apply spatial processing first and then temporal processing. Beamforming-matched filter power map with the target at 100 m is shown in Fig.6, SWRB-STAP processing power map with the target at 100 m is shown in Fig.7, Beamforming-matched filter power map with the target at 200 m is shown in Fig.8, SWRB-STAP processing power map with the target at 100 m is shown in Fig.9.

It can be observed from the comparison above that, when the target is completely buried in the wideband beamformer-matched-filter power map and cannot be discerned, the STAP processing still clearly reveals the target. Moreover, the reverberation region in the STAP output appears significantly darker, demonstrating that when a target has a nonzero radial velocity, STAP can separate the echo from clutter in the two-dimensional space–time domain, locking onto the target while suppressing reverberation. This performance surpasses that of cascaded space–time processing, as STAP maintains target detection even when the echo is weak. After independently filtering each fine-range cell, SWRB-STAP clearly locks onto the target at 100 m range and 60° bearing, with the reverberation region strongly suppressed—substantially outperforming the cascaded approach.

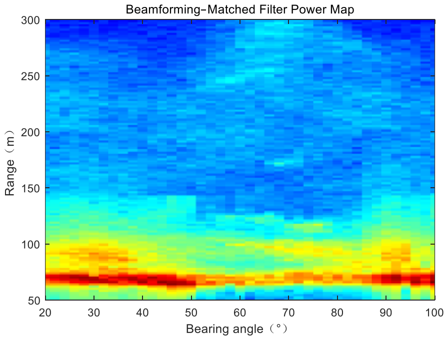

Fig 6. Beamforming-matched filter power map with the target at 100 m

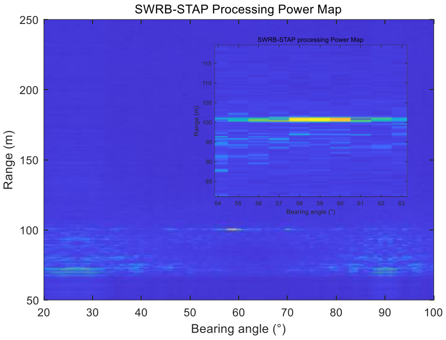

Fig 7. SWRB﹣STAP processing power map with the target at 100 m

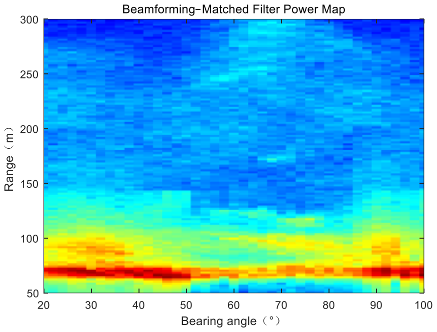

Fig 8. Beamforming-matched filter power map with the target at 200 m

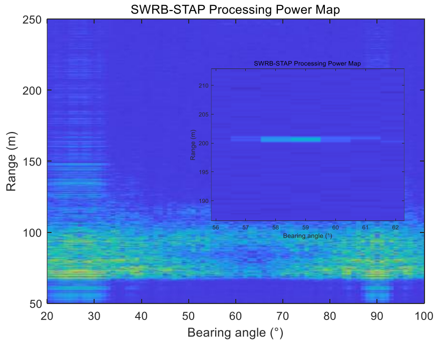

Fig 9. SWRB﹣STAP processing power map with the target at 200 m

IV. Conclusion

This paper introduces a Sliding‐Window Range–Bearing Scan STAP (SWRB‐STAP) method specifically designed to handle the nonstationary reverberation characteristics that vary with range in underwater active sonar. In this approach, fast‐time data are segmented into micro–range cells, and for each cell a local covariance estimate is computed using only its adjacent training window. This strategy adaptively captures reverberation statistics at different distances and effectively compensates for the modeling bias introduced by conventional one-shot, global covariance estimation. After performing narrowband STAP filtering in parallel within each micro–range cell, the resulting two-dimensional range–bearing power maps are concatenated to provide continuous reverberation suppression and target direction information. Semi-physical/synthetic experiments—using real reverberation measurements from Qiandao Lake with superimposed LFM target echoes—show that the cascaded space–time processing scheme leaves targets in strong reverberation zones almost undetectable, whereas SWRB-STAP stably locks onto the target and dramatically suppresses reverberation. Overall, SWRB-STAP exhibits a significant advantage in detection accuracy and is particularly well-suited for underwater target detection in shallow to mid-depth waters with complex reverberation. Future work will focus on extending the SWRB-STAP framework to broadband and multiband processing to accommodate multi-scale reverberation features, as well as on online adaptive parameter optimization—using techniques such as online learning or deep models to adjust sliding-window size and the number of guard/training cells—which is expected to further enhance algorithm performance and robustness.

V. Acknowledgment

This work was supported by the National Natural Science Foundation of China under Grant No. 62431023, the Stable Supporting Fund of NationalKey Laboratory of Underwater Acoustic Technology under Grant No. JCKYS2023604SSJS010. and Shanghai Aerospace Science Technology Innovation Foundation under Grant No. SAST2022-011.

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