International Journal of Engineering Research and Technology. ISSN 0974-3154, Volume 12, Number 12 (2019), pp. 2640-2654
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Array-Impulse-Pair Selection assisted STAP Model for Efficient Clutter Suppression and Jamming Resilience in Moving Sea-target Detection

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Abstract

In this paper, we proposed a novel and robust enhanced Space-Time Adaptive Process (STAP) assisted moving sea-target detection model. Unlike conventional approaches, our proposed method implements an enhanced STAP with optimal Antenna-Pulse Selection (APS) that reduces space-time subspace training impulse requirement for clutter covariance matrix estimation. To perform optimal APS provision at first we have performed Space Spectrum Correlation Coefficient (SSCC) estimation, which has been further processed for the optimal Antenna-Impulse Pair Selection that approximates clutter covariance matrix to achieve enhanced Signal-to-Clutter plus Noise Ratio (SCNR). Here, the use of SSCC helps achieving optimal separation between target signal and clutter subspace or allied clutter Fourier basis. Additionally, it suppresses jamming and noise power components that eventually assist enabling accurate moving target detection. Thus, the proposed method justifies its robustness not only towards moving target detection under sea-clutter by suppressing clutter subspace, but also alleviates the problem of jamming. Hence, it enables secure, reliable and efficient moving target detection under sea-clutter. The overall proposed model has been developed based on impulse radar setup using MATLAB tool where, multiple moving targets are detected for the received signal impulses. The proposed method can be a potential solution for multiple moving target detection even under heterogeneous environment containing clutter, jamming attacks, noise and other interferences. Thus, it is well suited for moving small target detection under sea clutter for efficient coastal surveillance purposes.

Keywords: Moving Target Detection, Sea-Clutter Environment, Impulse Radar, Space Time Adaptive Process, Clutter-Suppression, Antenna, Pulse Pair Selection, Coastal Surveillance.

I. INTRODUCTION

In the last few years, the development of advanced imaging systems, signal processing techniques and hardware capabilities has enabled different solutions to meet major at hand demands pertaining to industries, scientific researches, civil and defense purposes. Amongst the major technologies signal processing has always been the dominant paradigm to serve up-surging demands. Amongst the critical application demands, surveillance and security systems have always attracted academia-industries as well as defence related stakeholders to achieve more efficient solution. Considering the contemporary global scenario where almost all nations are undergoing problems like terrorism, smuggling, illegal migration or infiltration etc. Amongst the different reasons causing aforesaid issues, migration or intrusion through sea-ways (intrusion through coastal) is the most causative factor. Additionally, for defense purposes detecting small moving object becomes very tedious task, especially under oceanic disturbances or wave's non-linearity. It motivates academia-industries to develop more efficient RADAR systems to achieve effective sea-target or object detection. The moving target detection becomes tedious in case of sea-clutter and jamming conditions. Thus, the development of robust moving sea-target (say, object) detection can be vital to detect and identify commercial vessels, defence vessels, oceanic-creature as well as intruders. It can help making optimal decision in real-time surveillance purposes.

In the last few years the development of highly advanced signal processing technologies has broadened the capabilities of radar systems to detect targets and monitor large range of geography. However, detecting small moving object, especially under non-linearity such as oceanic waves is a tedious task [1][2]. Dynamism in oceans or sea makes small maritime target detection very complicate that becomes even severe under clutter condition. As illustration, small objects such as boats, wood-log, ice-bergs, parts of the damaged plane or sea-wrecks, Rigid Inflatable Boats (RIBs) etc are small in size that makes detection difficult using conventional radar system [1-3][30]. To enable a robust target detection radar it is inevitable to alleviate the problems caused due to clutter which depends on the oceanic events, local weather condition such as wind speed, wind-direction, height of waves, and the grazing angle of radar, as well as jamming issues [1-3]. Oceanic echoes seem to possess sea-spikes that create significant clutter which makes target detection difficult [1] Furthermore, detection of the multiple targets moving at slow speed becomes even more complicated during sea-clutter, and hence requires optimal clutter suppression model [2]. Jamming situation which is intentionally employed by intruders, in conjunction with sea-clutter can make overall detection process tedious [6]. In such case designing a robust clutter suppression model with jammer resilience and noise-power cancellation can be of vital significance [1-6]. It has been considered as the motivation of the presented research work.

Considering moving target detection issues in sea-clutter, authors [3][4] proposed clutter modelling concept with different statistical distributions. However, non-linearity in clutter amplitude and jamming could not be incorporated using classical statistical modeling method. Additionally, numerous efforts have been made from academician as well as defense sector towards moving object or target detection under sea-clutter. Some of the key efforts were made by employing Spatio-Temporal Fourier Transform (STFT) that enables space as well as time domain analysis of the received signal to detect moving object [55-57]. However, its efficacy often remains suspicious under high clutter and jamming condition, which is very common and probable in current scenarios. Though, wavelet packet analysis, and Fourier analysis approaches have been applied for moving target detection [33], the use of both spatial as well as temporal features opens us further scope for enhancement [5][6]. Unlike conventional methods, the use of Space-Time Adaptive Processing (STAP) method because of its ability to process temporal as well as spatial subspace has gained significant attention across academia-industries to perform moving target detection [6-8][11][13][14][16][22-24]. It exhibits combining the different signals and/or allied pulses received from varied antenna-arrays to perform target detection accurately, even under clutter and jamming conditions [5-8]. Functionally, it applies the Clutter-plus-Noise Covariance Matrix (CCM) of the received signal which is processed for whitening before employing any Matched-Filter Detector (MFD). Since, CCM remains non-linear and unknown in case of coastal or oceanic clutter condition, STAP methods for example the Sample Matrix Inversion (SMI) can be able to retrieve the maximum-likelihood estimate of the CCM. However, it requires large number of Independent and Identically Distributed (IID) training data to estimate average Signal-to-Clutter-plus-Noise Ratio (SCNR) [5-8]. It used to outnumber the degree of freedom of the radar detector [8], which becomes highly complicate under non-homogenous and non-linear condition like sea (coastal)-environment [9]. Noticeably, the oceanic (sea) clutter and its heterogeneity along with limited training samples due to mobility can force classical STAP to undergo huge computational overheads [11][13][14][16][22-24]. Alleviating such complexities requires strengthening STAP to have higher interference suppression and clutter-signal separation capacity [8]. In majority of the clutter and interference suppression problems the radar systems used to be rank-deficient that enables STAP to function even with lower adaptive degree of freedom (DOF) requirements (in comparison to the DOF needed by array).

To achieve optimal performance by STAP, DOF can be reduced that can be vital for moving sea-object detection. To further augment it, certain pre-processing methods can be applied so as to retain only significant training data and eliminating the problem of clutter heterogeneity [10-14]. A recently proposed method called knowledge-assisted STAP (KSTAP) used a priori knowledge to enhance CCM convergence so as to make swift target detection [15–17]. Authors applied D3 algorithm [18] with the maximum likelihood detector to assist target detection without applying additional training data. Realizing large scale training data, recently authors proposed an image processing based STAP [19] where Principle Component Analysis (PCA) was used to transform feature data into lower dimensional feature subspace to estimate CCM for target detection [65]. The use of sparse recovery (SR) methods has been applied to assess clutter spectrum in the angle-Doppler plane to perform target separation [20][21]. Unfortunately, these methods are computationally complex, especially STAP based approaches which need a full-dimensional matrix inversion. As an alternate solution, authors [22][23] found that the use of sparse nature of the STAP filter weights can be more efficient to make target detection under clutter condition. It broadens the horizon for researcher to use efficient and adaptive STAP filter-weights for better detection accuracy. Though, numerous efforts have been made towards STAP based target detection under clutter; however no significant effort is available to detect multiple moving target under sea-clutter, noise and jamming conditions [19][22][23].

In this paper a highly robust and efficient Antenna-Pulse Pair Selection (APS) assisted STAP model is proposed for multiple (moving) sea-target detection in sea clutter and jamming probable environment. The proposed target detection model has been augmented with an enhanced ASP model that enables selecting an optimal set of Antenna-Pulse Pairs for each snapshot or time-range, which is then followed by using STAP to perform moving sea-target detection. Unlike a classical method [24], in which authors preferred employing antenna array distinctly rather he pulse train and considered using array information to suppress clutter information, we used antenna-pulse data obtained from participating sensors or receivers defined in terms of antenna number (M) and associated pulse number (N)for a snapshot to enable target detection and allied clutter suppression. Our proposed method enables reduction in both temporal as well as spatial subspace that ensures retention of the optimal sensors (say, radar array) and associated (subset of) antenna-pulse to achieve efficient clutter and jamming separation from the target signal. We have applied Spatial Spectrum Correlation Coefficient (SSCC) to support better APS provision in such manner that it could maximize or enhance the disparity between target signals and clutter (Fourier basis) and jammer components. SSCC has been designed in a manner that it intends to achieve higher SINR, even under clutter, noise and jamming condition. The use of SSCC enables higher SCNR output that results into efficient clutter suppression and sea-target detection. Considering realistic maritime navigation conditions, we have examined efficacy of the proposed target detection model to detect multiple moving targets. The overall proposed system has been developed using MATLAB tool, while its performance has been examined in terms of SINR, SINR losses, SINR Improvement Factor (SIF) etc. Overall simulation results affirmed efficiency of the proposed model for real-time coastal surveillance using pulse radar setup.

The remaining sections of the presented manuscript are given as follows. Section II discusses the related work, which is followed by research questions in Section III. Section IV presents the problem formulation, while the proposed model and its implementation is given in Section V. Simulation results obtained are given in Section VI, and the overall research conclusion is discussed in Section VII. References used in this study are given at the end of the manuscript.

II. RELATED WORK

Though, a large number of efforts have been made for target detection using radar systems; however clutter condition or other jamming conditions are different for the sea-condition or coastal environment. Therefore, understanding other existing approaches pertaining to object detection under sea-clutter can be significant to make novel contribution. With this motive, this section briefs some of the key literatures pertaining to sea-target detection under clutter conditions.

To detect small floating target in sea clutter, Li et al [25] proposed fractal-based detector where they applied normalized Hurst exponent to achieve better detection accuracy under un-uniform sea surface condition. Yang et al [26] in their work designed Orthogonal Projection method (OP) that performed target detection without using multiple radar systems. McDonald et al [27] exploited non-coherent integration, coherent integration and Kelly detector along with adaptive linear quadratic detector to detect floating target in sea clutter. Wavelet analysis was also explored for small target detection by Davidson et al [28], who found that the design or a wavelet determination model can be effective to assess scattered signal within the Doppler spectra of non-Gaussian sea clutter. Wavelet determination can be suitable feature extraction method to perform target detection in sea clutter. Similarly, Normalized Doppler Power Spectrum (NDPS) was applied by Li et al [29] for floating small target detection in sea clutter. Unlike [28, 29], Xu et al [30] focused on employing different polarization features including the relative surface scattering power, the relative volume scattering power, and the relative dihedral scattering power to perform target detection. This method enabled achieving a multi-polarization channel that created a 3-D feature detector for floating (small) target on sea-surface. However, these approaches are highly complex and possess computational overheads.

Due to low range of object floating, numerous targets might undergo undetected, Carretero-Moya et al [31] designed a Radon transform assisted heuristic concept for of low radar cross-section targets detection in sea clutter. Radon transform enabled sequential profile generation to detect small target in sea clutter. Shui et al [32] used three key features from the received signals; relative amplitude, relative Doppler peak height, and relative entropy of the Doppler amplitude spectrum to segment target in sea clutter. To enhance computation, authors [32] applied convex hull learning algorithm. To enhance detection, Duk et al [33] applied Stationary Wavelet Transforms (SWT); however it was well suited for the target detection in medium grazing angle X-band sea-clutter. Panagopoulos et al [34] applied three distinct signal processing techniques, like Signal Averaging (SA), Morphological Filtering (MF) and Time-Frequency Analysis (TFA) to detect target in sea clutter. Shi et al [35] used smoothed pseudo-Wigner-Ville distribution (SPWVD) model to enhance time frequency features of the given signal. SPWVD extracted time series information at the Cell-Under-Test (CUT) as well as reference cells near the CUT that helped estimating the differences between target returns and the TF pattern of sea clutter. Later authors substituted the target region from the sea clutter. Yang et al [36] used Butterworth high-pass filter to detect a small slowly moving target. Similarly, Jin et al [37] gave more preference to the Velocity Steering Vector (VSV) than the classical searching approaches to perform small slowly moving targets detection in spiky sea-clutter. For better feature learning, Leung et al [38] designed Genetic Algorithm (GA) based Artificial Neural Networks (ANN) to detect the target in sea clutter. In this method [38] GA was used to enhance signal reconstruction, while Radial Basis Function (RBF) was used as learning model (for sea-clutter feature learning). Hennessey et al [39] too used ANN for radar clutter modeling that effectively dealt with the inherent nonlinearity nature of the sea-clutter. RBF ANN learnt sea-clutter information to locate small moving target in sea clutter. Zuo et al [40] used time-frequency iteration decomposition based slow moving target detection in sea-clutter. Authors applied X-band sea echo with a weak simulated target to examine efficiency of the proposed method. Brekke et al [41] developed Probabilistic Data Association Filter with Amplitude Information (PDAFAI) which exploited conservative amplitude probabilities to detect small floating targets in sea-clutter. Guan et al [42] focused mainly on enhancing the signal analysis and developed Fractional Fourier transform (FRFT), by combining statistic as well as FRFT-based target detection method.

Considering the complexities caused due to dynamic waves, size of the target and sea clutter, Croney et al [43] recommended using clutter de-correlation method by employing fast antenna scanning followed by camera or direct-view storage-tube integration. This approach was found efficient towards small slow moving target detection under sea-clutter. Dong et al [44] applied revised Visual Attention Model (VAM) and the Anti-Vibration Pipeline-Filtering (AVPF) algorithm for maritime target detection. However, it could not guarantee accurate target detection and tracking under sea-clutter [45]. To achieve better accuracy Leung et al [46] modeled radar echoes retrieved from sea surface as nonlinear deterministic dynamical system. Obtaining the signal, authors [46] used two dynamic target detection systems using dynamical invariant also known as the attractor dimension to enable separation of target signal from sea clutter. Unlike classical linear prediction model Leung et al [47] proposed a nonlinear prediction (NLP) model to avoid clutter condition for better target detection. Undeniably, the nonlinearity and non-Gaussianity nature of clutter process enables NLP to suppress clutter efficiently.

Rodriguez et al [48] proposed the GLRT-based adaptive multi-frame detection scheme for multi-pixel targe detection. Authors modelled sea-clutter as the channel encompassing Gaussian noise added with the background Gaussian clutter with varying covariance matrix. Authors [49] applied spatial-temporal patches also called frames to obtain the specified target appearance that eventually helped in estimating background clutter. It encompassed the multi pixel Adaptive Subspace Detector (ASD) along with the Adaptive Multipixel Background-Plus-Noise Power Change Detector (AMBPNC) for multi pixel target detection in sea clutter. Zhao et al [50] developed Eigen value-based detection method where Eigen values of the covariance matrix were used to calculate the correlation amongst the signal retrieved. However, authors could not assess their efficacy over varying Doppler characteristics, which is common with target movement condition. In addition, clutter was not addressed. Gao et al [51] used Multi-Scale Adaptive Gray and Variance Difference (MSAGVD) to detect small target in sea-clutter. To alleviate the issue of false alarm under dynamic background condition, authors [52] used a multi-scale variance difference measures. Authors found that their approach with a threshold-adaptive segmentation can achieve better performance. Maresca et al [53] too made effort to alleviate clutter (sea waves) from who Doppler spectrum to enhance ship's detection accuracy by Sky-Wave Over-the-Horizon Radar (OTHR). In [54], Haykin et al applied the concept of Time-Frequency Analysis (TFA) by performing feature extraction and pattern classification for small target detection under dynamic background. For TFA authors [55] used Wigner-Ville distribution (WVD) by transforming echoes signal into a time-frequency image (time-varying nature of the received signal's spectral content of the iceberg). In addition, Hanning window function was used with Fourier transforms to detect moving object in sea- clutter. Baggenstoss et al [56] assessed different window sizes and their impact on detection accuracy. The use of Guassian noise helped detecting pulses of unknown duration, while windowing enabled suppressing multiple radio frequency interference [57].

Undeniably, numerous efforts have been made to detect moving target in sea clutter amongst then STFT based TFA has performed better. However no significant effort has been made on optimizing selection of STFT parameters to achieve better window analysis which can be significant for time-series analysis, especially for the small moving target detection in sea clutter. Though, above discussed approaches intended to achieve better clutter suppression and target detection; however majority of the existing approaches either focus on clutter suppression or Doppler analysis based target detection. On contrary, in contemporary conditions it is inevitable to detect moving target irrespective of size while assuring optimal clutter suppression, jamming attack-resilience even with low computational cost and training impulses. These gaps and allied scopes have been considered as the motive for this research work.

III. RESEARCH QUESTIONS

Considering overall research intends, scopes and allied prior-identified solutions, we have framed a few research questions. These research questions assess whether the proposed methodologies can achieve eventual goal or not. In other words, the overall proposed method intends to achieve optimal answers for the following research questions.

- ***RQ-1***Can the use of Space-Time Adaptive Processing (STAP) technique with adaptive weight and filter be effective to perform small moving target detection under sea clutter and jamming threats?
- ***RQ-2*** Can the use of an enhanced Antenna-Pulse-Pair Selection (APS) strategy be effective to reduce or approximate the CCM so as to achieve computationally efficient STAP for moving target detection in sea-clutter?
- ***RQ-3*** Can the strategic use of APS followed by SSCC with optimal CCM be efficient to suppress clutter subspace, noise and jammers to help optimal moving target detection under sea clutter?
- ***RQ-4*** Can the above stated (RQ-1 to RQ-4) methods as cumulative solution be effective to perform multiple moving target detection under sea-clutter and jamming threats for coastal surveillance?

IV. PROBLEM FORMULATION

The high pace rise in oceanic movement including sea-ways, sea-tourism, commercial sea-ways transportation, and more importantly the increased probability of smuggling, human trafficking and terrorism has alarmed associated stakeholders to develop more efficient and robust coastal surveillance systems for continuous monitoring and dynamic decision. Though, to achieve it numerous radar systems and allied signal processing techniques have been developed, the adverse coastal conditions such as dynamic wave patterns, non-linear sea-surface, clutter etc make major conventional radar systems confined. On the other hand, in the last few years intruders have been found applying jammer to deviate radar system that affects the detection accuracy. The detection becomes more challenging in case of small moving targets under clutter and jamming attack probability. This as a result can adversely affect overall target detection and dynamic decision capability for coastal surveillance. Though, few approaches like Doppler analysis assisted STFT have been designed for moving target detection, their efficacy has remained limited due to insufficient training data, varying locations, inappropriate clutter suppression, ambiguity between clutter and signal information, insufficient azimuth and elevation information etc. Considering these all facts, the use of STAP technique can be vital. The ability to process both space as well as time subspace enables STAP suitable for moving target detection in sea-clutter and jamming condition. STAP has been found robust to perform clutter suppression as well as jamming resilience, which can be of utmost significance for coastal surveillance purposes or allied moving small target detection. However, the conventional STAP methods require more training impulses and optimal antenna-array adjustment to achieve clutter suppression and associated target detection. Considering it as gap and resulting scope in this research paper the focus is made on developing a lightweight and efficient STAP model. The proposed adaptive STAP model has been designed by incorporating a robust APS model, which intends to select or retain significant or optimal Antenna-Pulse Pairs for each snapshot or received signal matrix (over M array and allied N pulses for each snapshot). The proposed APS model has been designed in such manner that it intends to achieve higher SCNR by performing or approximating CCM. To achieve it, at first SSCC has been obtained which has been followed by convex optimization and enhanced correlation assessment process, which eventually enables (optimal) clutter subspace (Clutter Fourier Basis) separation from target signal subspace. Noticeably, in proposed method SSCC intends to enhance SCNR output so as to achieve better clutter suppression without assuming target signal as clutter subspace components and avoiding jamming affect. It achieves optimal moving target detection, which has been justified for its ability to detect multiple moving targets detection under sea-clutter, noise and jamming conditions.

In the proposed model both space as well as time subspace has been reduced by performing optimal APS provision in each time-interval (say, snapshot or patch), which can enable it achieving accurate moving target detection. The proposed model has been developed as impulse radar setup solution where antenna-pulse data has been obtained from participating sensors with M antennas and N number of pulses each interval or period. Thus, the selected array-pulse pair is applied to perform STAP so as to detect multiple moving targets in sea-clutter. As signal model we consider clutter subspace, jammer and target signal subspace, where STAP with SSCC intends to separate clutter (nearest Fourier basis) and jamming subspace from target signal subspace. This process eventually achieves optimal small moving target detection in sea clutter without employing large temporal and spatial subspace information. It reduces computational overheads significantly thus making it more suitable for real time applications. The proposed method has been tested with multiple (here 3) moving targets in sea clutter environment and performance has been assessed. The detailed discussion of the proposed method is given in the sub-sequent section. A snippet of the proposed space-time processor used for moving target detection is given in Fig. 1. As depicted in Fig. 1, STP takes Doppler information along with the target angle (here, Azimuth information) at the receiver. Retrieving per snapshot of information containing data signal obtained through M pulses from N array elements, it estimates output as $Z = W^H X$. Thus, obtaining covariance matrix for each patch or snapshot, it assesses whether there is target available in each patch or snapshot. The detailed discussion of the proposed model is given in the sub-sequent section.

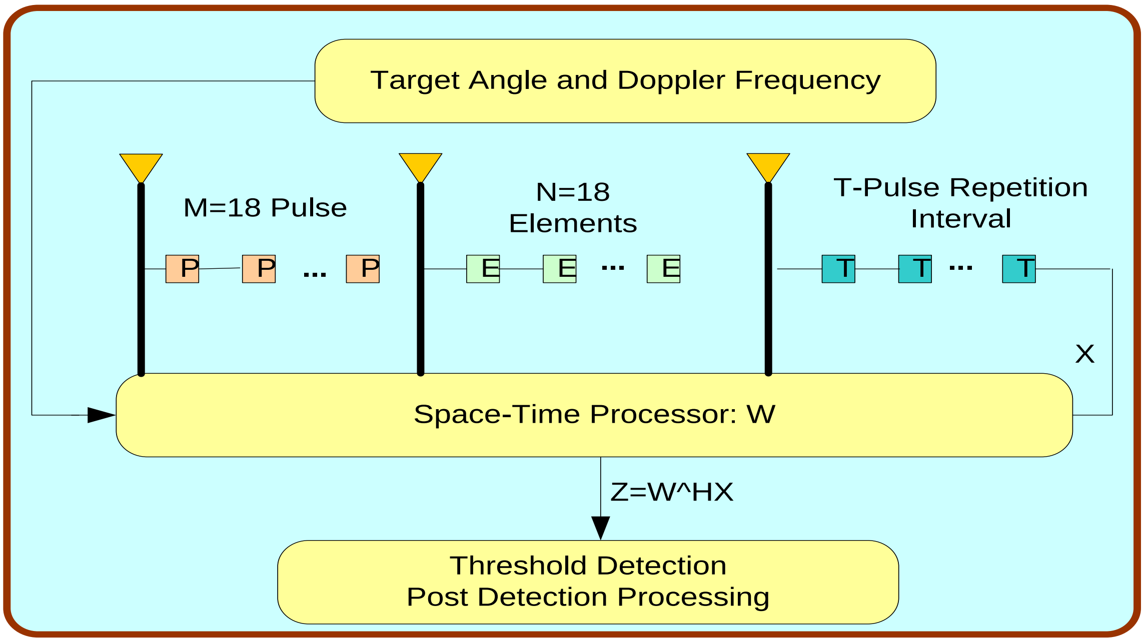

Fig. 1 Classical Space-Time processor used for moving target detection

V. OUR CONTRIBUTION

Considering the inevitable significance of a robust signal processing technique for radar signal detection this research primarily emphasizes on designing a novel and enhanced model, especially designed for moving object detection in sea clutter, which often undergoes significant interferences and clutter conditions. In addition, realizing the contemporary oceanic threats caused due to malicious intruders and respective activities such as jamming this research intends to design a robust signal processing technique which could achieve optimal object detection even under noise, interference, clutter and jamming conditions. Literatures reveal that unlike classical Fourier transform based approaches, the use of STAP can be of great significance to achieve optimal object detection even under aforesaid conditions. With this motive, in this paper a novel Adaptive STAP (ASTAP) model is developed that focuses on achieving optimal detection, clutter suppression and jamming resilience. This as a result can achieve optimal performance for real-time coastal surveillance using Pulse Doppler Radar (PDR) system. In our proposed sea-object detection model, we have obtained spatial spectrum correlation coefficient (SSCC) that characterizes the disparity between the target and the nearest cluster information or Fourier basis, also called clutter subspace. In addition, we introduce a novel Antenna Pulse Selection (APS) model that gives rise to the space time (spatio-temporal) configuration, which eventually enhances signal-to-clutter-noise ratio (SCNR) for better detection accuracy. The detailed discussion of the proposed model is given in the sub-sequent sections.

Before discussing the proposed Adaptive STAP based object detection under sea clutter and jamming conditions, a snippet of the signal model is discussed as follows:

A. Signal Model

In our proposed research a side-looking RADAR system has been considered possessing N antenna, which are placed uniformly placed with d as inter-element spacing. Consider that P be the scatterer patch on the RADAR surface level (say, RADAR ground level) possessing relative elevation angle θ and azimuth angle $\emptyset$ (w.r.t the centre of the array). Let, the RADAR antenna be of size (or distance) nd for $n = 0, \dots, N-1$ with reference to the array origin. In such cases, the signal retrieved by the antenna from P would be typically the phase shifted with reference to the origin. The phase shift can be obtained using (1).

$$n2\pi f_s = n\frac{2\pi}{\lambda} dcos\phi cos\theta \tag{1}$$

In (1), the parameter $f_s = \frac{d}{\lambda} cos\phi cos\theta \in \left[-{}^1/_2 \;\; {}^1/_2\right]$ signifies the normalized spatial frequency provided $d = \frac{\lambda}{2}$, where λ states the wavelength. Now, the spatial steering vector is (2).

$$a_s = \left[1, e^{j2\pi f_s}, \dots, e^{j(N-1)2\pi f_s}\right]^T \tag{2}$$

Being a PDR system, we estimate the Doppler frequency by performing phase comparison in between the echo signals obtained with pulse repetition interval $\tilde{T}$. Noticeably, the retrieved echo signal presents the Transmitted Coherent Pulse Train (TCPR) which is reflected back to the antenna for further processing. Now, the phase shift introduced by the object moving with the velocity of $v_p$is obtained as (3).

$$2\pi f_d = 2\pi\tilde{T}\frac{2v_p}{\lambda} cos\phi cos\theta \tag{3}$$

In (3), $f_d = \left(2v_p\frac{\tilde{T}}{\lambda}\right) cos\phi cos\theta$ states the normalized Doppler frequency (NDF). In such condition, the sequential steering vector with M consistent pulses can be obtained using (4).

$$a_t = \left[1, e^{j2\pi f_d}, \dots, e^{j(N-1)2\pi f_d}\right]^T \tag{4}$$

Now, the interleaved Spatio-Temporal steering vector can be obtained using (5).

$$a(\theta, \emptyset) = a_s \otimes a_t \tag{5}$$

Noticeably, in (5), $a(\theta, \emptyset) \in \mathbb{C}^{NM\times 1}$. Here, $\otimes$ states the Kronecker product. Consider that with an elevation angle θ, the total clutter echo signifies the period during the cumulative contributions made from the ground scatterers in $\emptyset$ (azimuth). Mathematically,

$$c(\theta) = \int_{\emptyset=0}^{2\pi} AD(\theta, \emptyset)G\,(\emptyset, \theta)a(\theta, \emptyset)d\emptyset \tag{6}$$

In (6), the variable A states the reflectivity, which in our case is hypothesized to be a circular complex Gaussian variable. The other variables $D(\theta, \emptyset)$ and $G(\emptyset, \theta)$ represents the retrieved and the transmitted directivity patterns, correspondingly.

Undeniably, in ASTAP model the pattern and allied trajectory information pertaining to the clutter spectrum, especially in the angle-Doppler $(f_s - f_d)$ plane can be of utmost significance to extract the vital information available on the clutter subspace. This in the later phase can be significant to suppress the clutter. With this motive, in the proposed PDR model, we defined the clutter trajectory as (7).

$$f_d = kf_s \tag{7}$$

In fact, considering coastal surveillance condition (for moving object or ship detection) above stated trajectory model signifies a straight line in the $f_d - f_s$ plane. In (7), the variable k signifies the slope with value given in (7).

$$k = \left(2v_p\frac{\tilde{T}}{d}\right) \tag{8}$$

In the proposed moving object detection model, we consider detection as the problem of hypothesis test that assess the presence of a potential target in certain received reflection patch. The received signal model for a unitary range augmentation can be defined as $x \in \mathbb{C}^{NM}$. With respect to the retrieved x, the null hypothesis H_0 can be defined as (9).

$$H_0: x = c + n \tag{9}$$

Simplifying the model, her onwards we assign c rather $c(u)$. In (9), the parameter n states the Additive Gaussian White Noise (AWGN) having power of σ_n^2. Now, we define the alternate hypothesis as (10).

$$H_1: x = \alpha t + c + n \tag{10}$$

In (10), the variable α states the complex amplitude of the moving target signal. The space-time (say, spatio-temporal) steering vector of the target signal $t \in \mathbb{C}^{NM\times 1}$ has been obtained using models derived in (2), (4) and (5) provided $f_s = \frac{d}{\lambda} cos\phi_t cos\theta_t$and $f_d = 2v_t\frac{\tilde{T}}{\lambda}$ for the sea (moving) target with θ_t and ϕ_t, moving with the radial velocity v_t. In our proposed model, we hypothesize that the comprising elements of the received signal x at antenna array are autonomous. Here, we define a matrix called Clutter-Plus-Noise-Covariance Matrix (CCM), Q as the addition of clutter components and noise covariance matrices. Mathematically, it is defined in (11).

$$Q = E\{xx^H\} = \sigma_n^2 I_{NM} + Q_c \tag{11}$$

In (11), the parameter Q_c signifies the clutter covariance matrix, which is always rank-deficient. Employing the Brennan's rule [5] we obtain the rank of the clutter component N_e as (12).

$$N_e = int\{N + k(M-1)\} \tag{12}$$

In (12), the component $int\{\quad\}$ states the sub-sequent integer number (say, nearest integer). Let, the clutter rank be N_e, then we obtain the clutter covariance matrix as (13).

$$Q_c = \sum_{i=1}^{N_e} \sigma_i^2\, e_i e_i^H = \sum_{j=1}^{N_e} P_j v_j v_j^H \tag{13}$$

In (13), the parameters e_i states the $i-$th Eigenvector, while allied Eigenvalue of Q_c is given by and σ_i^2. Here onwards, we state $e_i, i = 1, \dots, N_e$ as "Clutter Eigen Basis (CEB). Now, the clutter subspace is retrieved by N_e Fourier basis vectors

$v_j, j = 1, \ldots, N_e$ possessing the power coefficients P_j. Practically, the Fourier basis v_j possesses the same definition as the interleaved Spatio-Temporal steering vector a, defined in (5) under spatial and Doppler frequencies conditions. Following aforementioned condition, the two sets of the rank N_e basis vectors extents the similar clutter subspace. In other words $span(e_i, i = 1, \ldots, N_e) = span(v_j, j = 1, \ldots, N_e)$. Now, the individual Fourier basis vector can be defined as a linear combination of eigenbasis. Mathematically,

$$v_j = \sum_{i=1}^{N_e} \mu_i^j e_i \tag{14}$$

In our proposed model, we have applied adaptive matched filter (AMF) detector as discussed in [58]. Here, we get (15)

$$\frac{\left|v^H \hat{Q}^{-1} x\right|^2}{v^H \hat{Q}^{-1} v} \underset{\geq}{\leq} \mathcal{T} \tag{15}$$

In (15), the variable $\mathcal{T}$ states the threshold value, while v represents the scanning steering vector over $f_d - f_s$ (also called the angle-Doppler plane). Here, we calculate Q using the equation (16).

$$Q = \frac{1}{L} \sum_{l=1}^{L} x(l) x^H(l) \tag{16}$$

The above model functions with L coherent (homogeneous) training data, by following the hypothesis defined as H_0. Noticeably, the maximum value of (15) is obtained when $\mathrm{v} = \mathrm{t}$.

In our proposed sea-object detection model, we have obtained Spatial Spectrum Correlation Coefficient (SSCC) that characterizes the disparity between the target and the nearest cluster information or Fourier basis, also called clutter subspace. The detailed discussion of the proposed SSCC model is given in the sub-sequent section.

B. Spatial Spectrum Correlation Coefficient (SSCC)

In existing approaches, authors [59] have considered merely single interference condition to derive SSCC; however such methods can't be applicable for our considered sea-object detection under clutter, as it might undergo multiple interference conditions. Therefore, in our proposed model, we have employed the concept of clutter subspace to make its suitable for multiple interference conditions. The detailed discussion is given as follows:

1. CCM Matrix Vector Estimation

Considering the already retrieved clutter covariance matrix (CCM) in (12), in this work we further obtain the N_e Fourier basis vectors and transform it into equivalent matrix form called CCM-Matrix. Mathematically, the matrix vector is (17).

$$V_c \in \mathbb{C}^{MN \times N_e} \tag{17}$$

$$V_c = \left[v_1, v_2, \ldots, v_{N_e}\right]$$

Now, considering the scatterer patch as the diagonal element, i.e., $P = diag\left[P_1, \ldots, P_{N_e}\right]$, CCM can be redefined as (11).

$$Q = \sigma_n^2 I_{NM} + V_c P V_c^H \tag{18}$$

Now, implementing the Woodbury Matrix Identity [] to the inverse of CCM, we get (19).

$$Q^{-1} = \frac{1}{\sigma_n^2}\left(I_{NM} - V_c(\sigma_n^2 P^{-1} + V_c^H V_c)^{-1} V_c^H\right) \tag{19}$$

Realizing the fact that in coastal surveillance there can be the situation where sea clutter might be stronger than the noise components (i.e., $P_1 > \cdots > P_{N_e} \gg \sigma_n^2$), redefine (19) as (20).

$$Q^{-1} \simeq \frac{1}{\sigma_n^2}\left(I_{NM} - V_c(V_c^H V_c)^{-1} V_c^H\right) \tag{20}$$

Observing (20), it can be found with high clutter-to-noise ratio (CNR), inverse CCM Q^{-1} can approximate the clutter null-space and therefore the ASTAP weight vector is obtained using (21).

$$w_{opt} = \eta Q^{-1} t \simeq \frac{\eta}{\sigma_n^2}\left(I_{NM} - V_c(V_c^H V_c)^{-1} V_c^H\right) t \tag{21}$$

Factually, it behaves like interference Eigen-canceller [60]. In (21), the parameter $\eta = (tQ^{-1}t)^{-1/2}$ is independent of the output SCNR or vice versa. Here, we decompose the steering vector of the target signal t into two distinct perpendicular components. These are, the clutter subspace t_c and the null space $t_\perp$, Noticeably,

$$t_c = \left(V_c(V_c^H V_c)^{-1} V_c^H\right) t \tag{22}$$

$$t_\perp = \left(I_{NM} - V_c(V_c^H V_c)^{-1} V_c^H\right) t$$

In ASTAP model, the respective weight vector w_{opt} exists towards $t_\perp$. Now, we derive the SSCC parameter as the absolute value of the cosine of the angle between t and clutter subspace component t_c. Mathematically, SSCC is obtained as (23).

$$|\alpha| = |cos\vartheta| = \frac{t^H t_c}{\|t\|_2 \|t_c\|_2} \tag{23}$$

In our proposed model we limit the length of t as $\|t\|_2$ which is equivalent to the $\sqrt{MN}$, providing a condition that the PDR be possessing isotropic antenna elements. Since, the output of the signal-to-clutter-noise ratio (SCNR) is always proportional to the squared value of the SSCC, in our proposed model we replace t_c in (23) and obtain the output as the squared value given in (24). Mathematically,

$$|\alpha|^2 = \frac{|t^H V_c (V_c^H V_c)^{-1} V_c^H t|}{MN \|V_c (V_c^H V_c)^{-1} V_c^H t\|_2^2} \tag{24}$$

$$= \frac{1}{MN} t^H V_c (V_c^H V_c)^{-1} V_c^H t$$

Eventually, with (18) and (21), we estimate $SCNR_{Out}$ as (25).

$$SCNR_{Out} = \sigma_t^2 t^H Q^{-1} t \tag{25}$$

$$\simeq \frac{\sigma_t^2}{\sigma_n^2} t^H \left(I_{NM} - V_c (V_c^H V_c)^{-1} V_c^H t\right)$$

$$\simeq SNR.MN(1 - |\alpha|^2)$$

In (25), the parameter σ_t^2 signifies the signal strength of the moving target or the power of the target signal. The respective signal to noise ratio SNR is given as $SNR = \frac{\sigma_t^2}{\sigma_n^2}$. Observing (25), it can be found that the eventual $SCNR_{Out}$ relies on the two key factors. First, the degree of freedom or MN, while second factor is $|\alpha|^2$. In case of MN as fixed value, performance can be enhanced by varying the spatio-temporal configuration that can reduce the value of SSCC. It signifies that SSCC can define the impact of the space-time geometry on the adaptive filtering performance. This as a result gives the scope to identify optimal metric, which can be achieved by means of the optimal antenna-pulse selection provision. The detailed discussion of the APS model is given in the next section. Before discussing the APS provision, we have derived a determinant model so as to assist optimal APS for sea-object detection under clutter.

2. *Determinant Modelling*

As discussed in the previous section, the matrix–vector model obtained in (24) can't be the optimal one for APS, and therefore with this motive, we have formulated a new model for SSCC which exploits (24) to obtain the matrix determinants. Consider that the clutter cross-correlation matrix be $D_c \in \mathbb{C}^{N_e \times N_e}$. Matematically,

$$D_c = V_c^H V_c = \begin{bmatrix} \rho_{11} & \rho_{12} & & \rho_{1N_e} \\ \rho_{21} & \rho_{22} & & \rho_{2N_e} \\ \cdots & \cdots & \cdots & \cdots \\ \rho_{N_e1} & \rho_{N_e2} & & \rho_{N_eN_e} \end{bmatrix} \quad (26)$$

In (26), the parameter $\rho_{11} = v_i^H v_j$ for $i, j = 1, \ldots, N_e$.

Noticeably, the Fourier basis vectors $[\hat{v}_j]$ as defined in (43) can't be universally orthogonal in case of realistic sea clutter condition, and therefore there is not need to solve or simplify D_c as I_{N_e} to achieve generalization. With vector $V_t = [t, v_1, v_2, \ldots, v_{N_e}]$, the Target Plus Clutter Cross-Correlation Matrix (TCCCM) can b obtained as (27), where $D_t \in \mathbb{C}^{(N_e+1)\times(N_e+1)}$.

$$D_t = V_t V_t^H \quad (27)$$

$$D_t = V_t V_t^H = \begin{bmatrix} \rho_{tt} & \rho_{t1} & \cdots & \rho_{tN_e} \\ \rho_{1t} & \rho_{11} & \cdots & \rho_{1N_e} \\ \cdots & \cdots & \cdots & \cdots \\ \rho_{N_et} & \rho_{N_e1} & \cdots & \rho_{N_eN_e} \end{bmatrix}$$

$$= \begin{bmatrix} MN & t^H V_c \\ V_c^T t & D_c \end{bmatrix}$$

In equation (27), $\rho_{tj} = \rho_{jt}^* = t^H V_j$ for $j = 1, \ldots, N_e$ and $\rho_{tt} = t^H t = MN$, hypothesizing MN as the antenna-pulse pairs. Now, employing the derived determinant model in (27) we get (28).

$$|D_t| = |D_c|(MN - t^H V_c D_c^{-1} V_c^H t) \quad (28)$$

$$t^H V_c D_c^{-1} V_c^H t = MN - \frac{|D_t|}{|D_c|} \quad (29)$$

Now, employing (26) and (29) into (24), the value of SSCC can be obtained in the form of the ratio of matrix determinants, given in (30).

$$|\alpha|^2 = \frac{1}{MN} t^H V_c D_c^{-1} V_c^H t = 1 - \frac{|D_t|}{MN|D_c|} \quad (30)$$

For single interference scenario, $N_e = 1$ and hence the CCM in (26) and (27) is further derived to $D_c = \rho_{11} = MN$. Thus, the TCCCM is obtained as (31). Mathematically,

$$D_t = \begin{bmatrix} MN & \rho_{t1} \\ \rho_{1t} & MN \end{bmatrix} \quad (31)$$

$$SCNR_{out} \cong SNR.MN(1 - |\alpha|^2) \doteq SNR.\frac{|D_t|}{|D_c|} \quad (32)$$

Observing (32) and (25), it can be found that the both are equivalent; however there exist no distinct linear reliance in between the number of selected antenna-pulse pairs and eventual performance as depicted in (32). Furthermore, it reveals the non-linear relationship between the degree of freedom and the eventual output $SCNR_{out}$. To further enhance the clutter suppression for accurate moving object detection, in this paper we have introduced a novel APS model that intends to optimize or enhance the $SCNR_{out}$ in (32). The detailed discussion of the proposed APS model is given as follows.

3. *SSCC assisted Enhanced APS for Sea-Clutter Suppression*

As stated, in our proposed model to achieve better sea-object detection we focus on enabling clutter suppression. To achieve it, we formulate our model to achieve maximum value for $SCNR_{out}$ by introducing APS provision.

APS can be achieved by means of two distinct methods. These are:

1. *Convex Programming*
2. *Augmented Correlation Assessment*

A snippet of these methods is given as follows:

a). Convex Programming

In this method a binary selection vector $z \in \{0,1\}^{MN}$ is introduced where '1' states that the allied antenna-pulse pair is selected. On the other hand, the value "0' signifies that the antenna-pulse pair is abandoned. With this condition, we obtain the CCMs for the selected sub-array using (33).

$$D_c(z) = V_c^H diag(z) V_c \quad (33)$$
$$D_t(z) = V_t^H diag(z) V_t$$

Noticeably, here we use the two matrices V_c and V_t, which are obtained by means of the equations (17) and (27), respectively. $D_c(z)$ the one of the CCM doesn't remain as an identity matrix once employing APS selection; though the N_e clutter basis vectors remains orthogonal. Because of this reason we avoided simplifying D_c as I_{N_e} in (26). Now, the output $SCNR_{out}$ of the selected configuration is presented as (34).

$$SCNR_{out} = SNR.\frac{|D_t(z)|}{|D_c(z)|} = SNR.\frac{|V_t^H diag(z) V_t|}{|V_c^H diag(z) V_c|} \quad (34)$$

As already stated, in our proposed method APS has been considered as the problem of enhancing the $SCNR_{out}$, which can be achieved by means of the objective function defined in (35).

$$\underset{z}{min} \frac{|D_c(z)|}{|D_t(z)|} \quad (35)$$

$$\text{s.t. } z \in \{0,1\}^{MN}$$

Here, in the proposed convex optimization problem we intend to achieve the objective function equal to the $Max_z SCNR_{out}$. It reveals the global minimiser as a vector containing all 1's, provided there is no limit for the number of selected entries. In ASTAP based RADAR systems, it is must to match the degree of freedom to the training data and therefore in our proposed model, we have assigned the total number of selected antenna-pulse pairs as K , where L be the total training data. Mathematically, $L = 2K$. Thus, the overall optimization problem turns into (36).

$$\min_{z} \frac{|D_c(z)|}{|D_t(z)|} \quad (36)$$

$$\text{s.t. } z \in \{0,1\}^{MN}$$

$$1^T z = K.$$

Now, we define $S = \{z: z \in [0,1]\}^{MN}$ which embodies the extreme points of the polytope defined as $D = \{z: 0 \preccurlyeq z \preccurlyeq 1\}$ with $z \in S$ and $z \in D$. As the components of the objective function $D_c(z)$ and $D_t(z)$ are non-negative and fixed the logarithm function increases monotonically that forces (36) to get conserved to the problem defined in (37).

$$\min_{z} log(|D_c(z)|) - log(|D_t(z)|) \quad (37)$$

$$\text{s.t. } 1^T z = K$$

$$z \in D$$

The objective function derived in (37) states the disparity in between the two concave functions, which can e solved by applying certain convex–concave methods that enables the function to converge at a fixed point signifying the global optimum [61]. In our proposed method we have applied convex concave programming concept [62] to perform optimization. A snippet of the applied optimization model is given as follows. In our proposed model, we define a concave function $f(z) = log(|D_c(z)|)$, which is approximated repeatedly by means of corresponding 1st order Taylor decomposition. For $(K+1)$ th iteration, we get (38). Mathematically,

$$f(z) \simeq \hat{f}(z) = f\left(z^{(k)}\right) + \nabla f\left(z^{(k)}\right)^T \left(z - z^{(k)}\right) \quad (38)$$

Noticeably, the jth entry of $\nabla f\left(z^{(k)}\right)$ would be (39), where $tr\{.\}$ employs the trace of the matrix, while $v_{c,j} \in \mathbb{C}^{N_1 \times 1}$ signifies the jth raw vector of v_c.

$$\nabla f_j\left(z^{(k)}\right) = tr\left\{D_c^{-1}\left(z^{(k)}\right)\left(v_{c,j} v_{c,j}^H\right)\right\} \quad (39)$$

Now, replacing the components obtained in (38), (39) into (37), while ignoring the constant components, we obtain the $(k+1)$ th iteration as (40).

$$\min_{z} \nabla f\left(z^{(k)}\right)^T - log(|D_t(z)|) \quad (40)$$

$$\text{s.t. } 1^T z = K$$

$$z \in D$$

Typically, the global optimum solution of any convex programming exists on the edge of the polytope D [63], which can be highly sparse and not inevitable to be the binary. In addition, it can be slower in nature. To alleviate such issues, certain local heuristic models can be applied to obtain the local optimum binary solutions. To achieve it, the conventional Gaussian randomization model has been modified to achieve a binary solution. In this work an arbitrary vector ξ is considered which is assumed to have each component $\xi_i \sim \mathcal{N}\left(\hat{z}, diag(\varepsilon_i)\right)$. The average of the $\hat{z}$ gives the optimal solution of (40) and the parameter ε_i states the variance of the i −th entry ξ_i. Retrieving ξ, the initial k-largest entries can be assigned to 1, while making others as 0 so as to generate the feasible points. Furthermore, the sampling can be continues in such manner it yields the best objective.

b). Augmented Correlation Assessment

As discussed in above section, convex concave programming needs solving multiple convex optimization problems that eventually can impose significantly large computational complexity. To alleviate this problem in this paper we have proposed an enhanced correlation measurement model using recommendation made in [64]. In fact, our proposed correlation assessment model behaves as a greedy search algorithm which has the well-justified ability to solve combinatorial optimization problems. In our considered Augmented Correlation Assessment model, at first we consider all antenna pulse pairs which is then processed with a backward search method that helps discarding the antenna-pulse pair that results the minimum objective value as defined in (36) iteratively for each available antenna-pulse pairs. Realizing the sea-clutter condition with multiple targets it becomes inevitable to retrieve the sparsest space-time configuration. On contrary, as already discussed that $SCNR_{out}$ increases monotonically as per increase in the number of selected antenna-pulse pairs, the use of our proposed augmented correlation assessment can be an effective solution. A snippet of the proposed correlation measurement model is given as follows:

Phase-1 Select all antenna-pulse pairs, with $z = 1$, by initialization iteration number k=1.

Assign $\beta^{(1)} = [1, \ldots, MN]$

Phase-2 For each $l = 1: MN - k + 1$

Assign $\hat{z} = z$ and $\hat{z}^{(1)}(l) = 0$, Estimate the value $r(l) = \frac{|D_c(\hat{z})|}{|D_t(z)|}$

End

Phase-3 Estimate the value of $i = arg \min_{l=1,\dots,MN-K+1} r(l)$

Phase-4 Assign $z\left(\beta^{(1)}(l)\right) = 0$, update

$$\beta^{(k+1)} = \frac{\beta^{(k)}}{\beta^{(k)}(i)} = \{n \in \beta^{(k)}, n \neq \beta^{(k)}(i)\} \tag{41}$$

Phase-5 $k = k + 1$, if $k = MN - k$, then stop the process, else go back to phase-2. Thus, the stopping criteria considered in our method ensures minimization in SCNR output value, and hence achieves better detection. Unlike classical methods where ASP is done for each of the angle-Doppler bin, the correlation analysis model avoids it and ensures computationally efficient moving sea-object detection under clutter. In our proposed model, we have applied Eigen basis function to characterize the clutter subspace, which given better performance than the Fourier analysis methods, which is often found suffering due to leakage effect. In this paper we perform antenna-pulse selection by performing element-wise multiplication. In other words, $\hat{v}_j = z \odot v_{j\in 1,2,\dots,N_e}$ .It states that the clutter subspace can be defined as $\hat{v}_j, j = 1,2,\dots,N_e$, and thus, $\widehat{V_c} = [\hat{v}_1, \dots, \hat{v}_{N_e}]$. Now, replacing the value of (14) into $\hat{v}_j$, we get

$$\hat{v}_j = \sum_{i=1}^{N_e} \mu_i^j (z \odot e_i) = \sum_{i=1}^{N_e} \mu_i^j \widehat{e_i}, j = 1, \dots, N_e \tag{42}$$

The selected Eigenbasis $\hat{E}_c = [\widehat{e_i}, \dots, \widehat{e_{N_e}}]$. Thus, V_c can be substituted by E_c and hence $V_c = [E_c, t]$ can be applied to perform APS. Noticeably, the sets of the precise clutter basis $e_{i\in 1,2,\dots,N_e}$ and $v_{j\in 1,2,\dots,N_e}$ are not known as a prior and therefore we have applied Fourier analysis method, which obtains it for each cell under test. Mathematically,

$$\hat{v} = arg \max_{v} |v^H x| \tag{43}$$

Thus, the power coefficient would be obtained as $\hat{P} = |\hat{v}^H x|^2$. In this model, the steering vector V scans overall angle-Doppler plane, which is often covered by MN resolution grids possessing N and M spatial and Doppler normalized frequencies, correspondingly.

VI. RESULTS AND DISCUSSION

To assess the efficacy of the proposed system, a simulation model for impulse radar system was developed. The designed radar system was deployed with multiple arrays distributed uniformly. In addition, we considered $M \times N$ configuration where M was the number of arrays while N stated the number of pulses and thus for each range the sensor obtained MN information to be processed for detection. The simulation model was designed in such manner that it performed detection for each sub-configuration after achieving optimization in APS. We considered three different targets for which Azimuth and elevation angles, Doppler frequency, Spatial Steering Vectors, Doppler Steering Vectors and Space-Time Steering Vectors were obtained. Noticeably, these parameters were measured distinctly for each target. As discussed in the previous section, in this paper both clutter as well as jamming were taken into consideration for which clutter covariance matrix as well as jamming covariance matrix are obtained distinctly, which are added with the target signal subspace. Thus, with such mixture of the different components, our proposed model intends to implement SSCC followed by APS to separate clutter Fourier basis and jamming subspace from the target signal to perform accurate target detection. To perform clutter covariance matrix at first the spatial and Doppler Frequencies for k-th clutter patch was obtained, which was then followed by normalizing the Doppler frequency of the k-th clutter patch. Similarly, Steering vector were assigned to the clutter patches. Noticeably, in this model steering vectors were assigned to all subspaces including spatial steering vector (SSV), temporal steering vector (TSV) and space-time steering vector (STSV). Noticeably, to generate final clutter covariance matrix of each patch or the signal retrieved using Kronecker tensor product amongst $STSV$, STSV transpose and Clutter to Noise Ratio (CNR). Similarly, jamming covariance matrix has been obtained by processing spatial frequency of the jammer and spatial steering vector of that specific jammer for the specific azimuth or allied training impulse. Thus, obtaining CCM, jamming covariance matrix and target signal a combined signal was obtained at the radar sensor, which was further processed for SSCC and APS so as to separate target signal from the nearest jamming and clutter Fourier basis function. Some of the key (simulation) design parameters are given in Table 1.

Table 1. Radar Operating parameters

Parameters	Values
Radar Operating Frequency	450 MHz
Peak Transmitter Power	200 kW
PRF	300 Hz
Number of pulses per Pulse Received Impulse (PRI) or M	18
PRI (Hz)	1/300
Number of Array Antenna N	18
Speed of light	299792458 m/s.
Operating wavelength (λ)	299792458/Operating frequency =299792458/4500000000 =0.06 m
Inter-element spacing (d)	$(\lambda/2)$

Noticeably, to generate clutter patch, we considered the following key parameters.

Table-2. Clutter patch geometry specification

Parameters	Values
Number of clutter patches uniformly distributed in azimuth	360
(clutter) range of interest in meters	13000
Azimuth angle increment in radium	$2\pi/360$
Radar range resolution	c/2/B
Earth radius	6370000
Effective Earth Radius in meters	4/3*Earth radius
Grazing angle at the clutter patch in radium	asin(platform altitude/ (clutter) range of interest)
Terrain-dependent reflectivity factor	$10^{\left(\frac{-3}{10}\right)}$
Depression angle is equal to grazing angle for flat earth model	asin(platform altitude/ (clutter) range of interest)

As already stated, in the proposed work, three distinct targets were deployed to be detected. The target positions and their respective relative power (dB) are presented in Fig. 1. The relative Doppler Frequencies and corresponding relative power can be visualized through Fig. 1. As illustrated in Fig. 1, the targets are placed at the Doppler Frequency of 100 Hz, and 50 Hz, while the azimuth is obtained as 0^0, -0.5^0 and 1^0. It depicts that all three targets are located very close to get detected by the radar system with low grazing angle. Noticeably, the main lobes are at the target positions, while the side-lobe clutters have been significantly reduced. Similarly, the other interference, noise and jamming components are reduced significantly, even below the thermal noise level at the output. That makes it efficient in target to clutter separation for better detection accuracy.

The simulation output for the principle cuts at the different Azimuth and Doppler frequency is presented in Fig. 2. As shown in the simulation output (Fig. 2), the result possesses multiple principle cuts, encompassing principle or primary at the targets. Noticeably, the side-lobes clutter possesses the similar Doppler as the target. On contrary, the secondary cut shows Doppler's response at the target DOA or Azimuth. Here, it must be noted that the patterns exhibit the condensed side lobe values for both Azimuth as well as Doppler values. It exhibits very minute SNR loss.

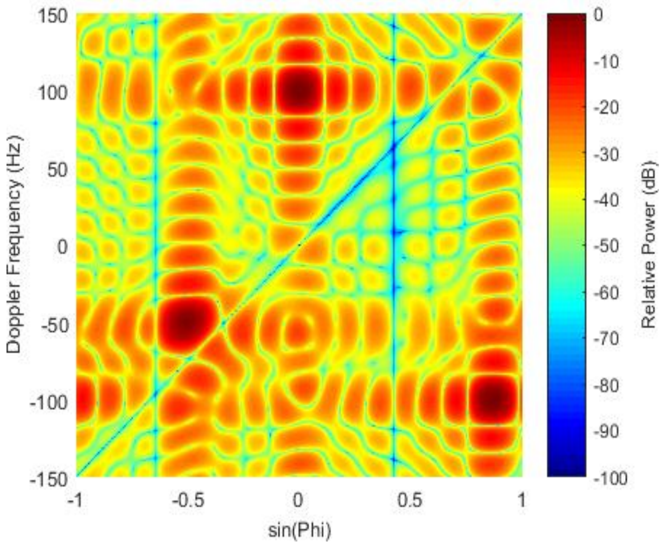

Fig. 1 Target pattern and allied power spectrum

Fig. 3 presents the comparative SINR over TDF. Noticeably, unlike Tapered Fully Adaptive STAP model where weight vectors are estimated using classical mathematical approach for each single target Doppler, our proposed method considers total covariance matrix including target signals, clutters, jammers and associated noise components, and cumulative Space-Time Steering Vector (STSV). It makes computation more effective to assist multiple target detection simultaneously.

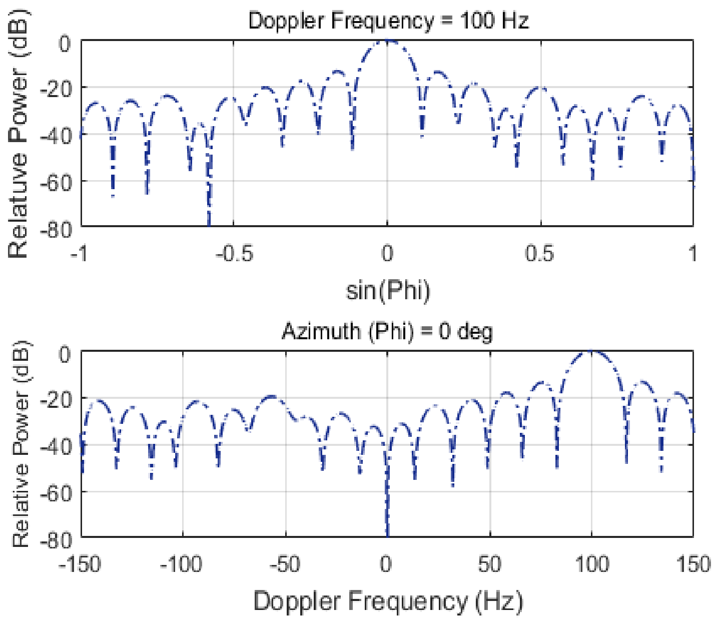

Fig. 2 Depiction of the principle cuts at the different Azimuth and Doppler frequency

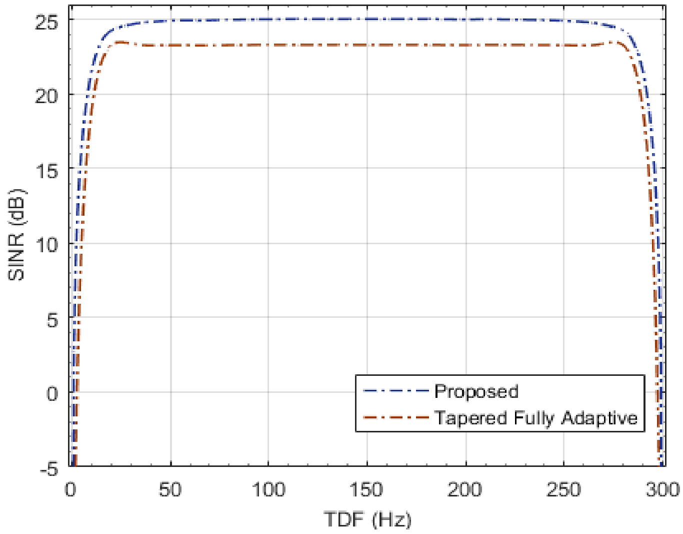

Fig. 3 Depiction of the comparative SINR variation over Targets Doppler Frequency (TDF) (received at the radar sensor)

Additionally, the proposed method achieves optimal SINR performance (curve) as compared to classical Adaptive STAP methods (here, called Tapered Fully Adaptive STAP). Fig. 4 presents SINR losses over varying TDF values for efficient multiple target detection under clutter. Simulation result (Fig. 4) reveals that the Fully Adaptive STAP model undergoes SINR losses at Doppler space, which is probable especially at 0 dB. As depicted the classical Fully Adapted STAP undergoes SINR losses, especially under straddling losses. On contrary, the employed filter design in the proposed method reduces SINR losses even under straddling losses, which is common in case of sea-clutter and even airborne conditions. Fig. 6 depicts the SINR enhancement by our proposed moving target detection system. To assess SINR enhancement using proposed model, we derived a parameter named SINR Improvement Factor (SIF). Noticeably, we measured SIF as the ratio of the SINR obtained by proposed model to the Input Interference-to-Noise-Ratio on a single element for a single pulse. Noticeably, here for simulation we used input interference-to-noise ratio as 48 dB, while CNR was maintained at 38 dB and associated jamming –to-noise ratio (JMR) was considered 38 dB for each target.

We estimated SIF with Elevation and Azimuth angle of 0^0. The simulation result (Fig. 6) depicts that the proposed model achieves higher SINR of 76 dB which is more than the tapered Fully Adaptive STAP. It exhibits that the proposed model can be more effective to detect any moving target under sea clutter condition, by enabling optimal clutter separation and jamming resilience.

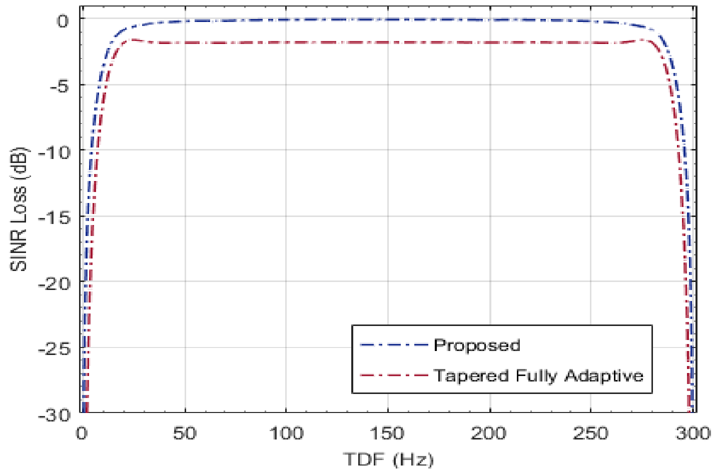

Fig. 4 Depiction of the comparative SINR losses over TDF (received at the radar sensor)

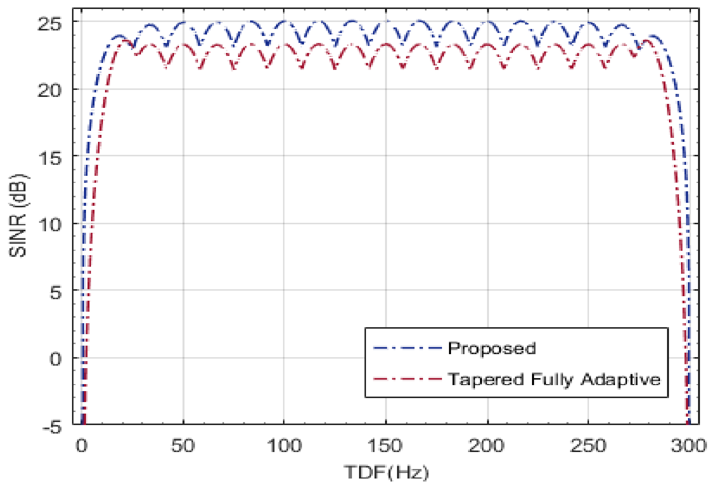

Fig. 5 Depiction of the comparative SINR performance over TDF (under clutter and Doppler straddling losses)

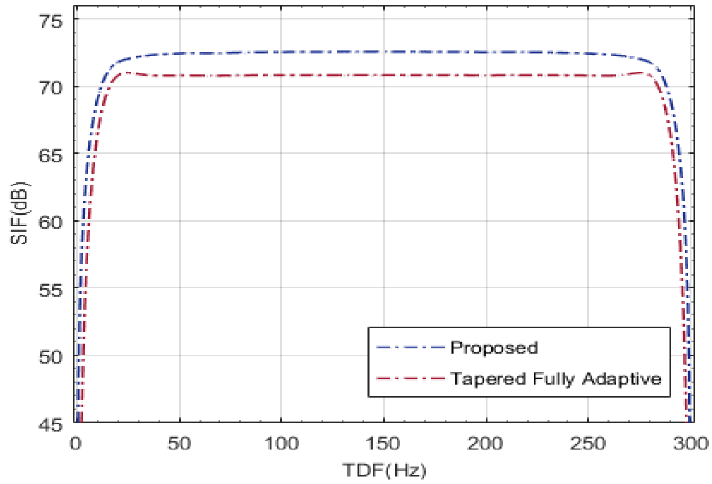

Fig. 6 Depiction of the SINR Improvement Factor (SIF) over TDF

VII. CONCLUSION

Considering the significance of a robust and efficient moving target detection model under sea-clutter, in this research the focus was made on exploiting efficacy of space time adaptive processing (STAP) method and impulse radar technologies. However, realizing the fact that the conventional STAP method requires high space as well as temporal subspace (impulse) information also called training impulse to perform detection, in this research at first effort was made on reducing time-space subspace dimension. To achieve it, at first spatial spectrum correlation coefficient (SSCC) estimation was performed that enabled an optimal Array-Pulse Pair Selection (APS). Consequently, it resulted into low dimensional array-impulse requirements to perform further clutter suppression and the target detection. Such value additions enabled proposed method to achieve time-efficient multiple targets detection under sea-clutter and jamming probability. Noticeably, this research employed convex optimization concept along with an enhanced clutter covariance matrix information which enabled target detection more efficiently. The use of SSCC enhanced Signal-to-Clutter-Noise Ratio (SCNR) output which eventually strengthened clutter suppression and hence more effective target detection under clutter and jamming conditions. The proposed moving (oceanic) small target detection model can be well suited for pulse radar system with strategically defined sensors or receiving arrays. The inclusion of SSCC assisted ASP followed by clutter suppression and, noise and jamming resilience ability make proposed model suitable for real-time coastal surveillance where radar has to deal with heterogeneous clutter conditions. The MATLAB based simulation has affirmed robustness of the proposed system towards multiple moving target detection in sea-clutter environment.

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