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A NORMALIZED FRACTIONALLY LOWER-ORDER MOMENT ALGORITHM FOR SPACE-TIME ADAPTIVE PROCESSING

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Abstract— **A new space-time adaptive processing algorithm is proposed for clutter suppression in phased array radar systems. In contrast to the commonly used normalized least mean square (NLMS) algorithm which uses the second order moments of the data for adaptation, the proposed method uses the lower order moments of the data to adapt the weight coefficients. The normalization is also performed based on the data sample dispersion rather than the variance. Processing results using simulated and measured data show that the proposed algorithm converges faster than the NLMS algorithms in Gaussian and non-Gaussian clutter environments. It also provides better clutter suppression than the NLMS algorithm under heavy-tailed, impulsive, non-Gaussian environments. It in turn improves the target detection performance.**

I. INTRODUCTION

Space-time adaptive processing refers to combined spatial beamforming and temporal Doppler filtering of radar returns in phased array antenna systems. It uses multiple antenna elements followed by tapped-delay-lines to coherently process multiple pulses thus providing superior ability to suppress jammers and clutters while preserving desired signal target [1]. Since its introduction in 1973, STAP has been rigorously researched and has been proven to provide significant performance gain in interference suppression and target detection. With the recent advance in digital signal processors (DSP), STAP has found wide spread application in airborne and ship-borne radar systems and space-borne satellites.

Many STAP algorithms dealt with common scenarios where clutters and noises are complex Gaussian, which leads to mathematically tractable solutions [2]. However, recent studies and field measurements have found [3]– [9] that heavy-tailed non-Gaussian clutters and noises often occur in backscatters from mountain tops, dense forest canopy, rough sea surfaces, and manmade concrete objects, etc. These radar clutters are spiky, impulsive in nature and cause significant performance degradation in STAP and target detection. Many technical issues still remain unsolved for non-Gaussian environments.

Several statistical models have been used to describe the impulsive non-Gaussian clutter environment including the compound K [3], [4] and complex alpha-stable [6]–[8]. The compound complex Gaussian model is a popular approach, where the clutter/noise process is the product of two random processes: $X = \sqrt{\tau} \cdot G$, with τ being the texture and G the speckle . If τ follows the Gamma distribution and G is complex Gaussian, then the envelop of $X = \sqrt{\tau} \cdot G$ will be the compound K distribution with the probability density function (pdf) given as [3], [4]

$$f_R(r) = \frac{2}{\sigma\Gamma(\nu)} \left(\frac{r}{2\sigma}\right)^{\nu} K_{\nu-1}\left(\frac{r}{2\nu}\right) \qquad (1)$$

where $K_\nu()$ is the modified Bessel Function of the second kind of order ν, and ν is the shape parameter. The function $\Gamma()$ is a Gamma function. The pdf of the compound K distribution is plotted in Fig. 1. The tails of the compound K pdfs are much higher than the Rayleigh distribution which is the envelope pdf of the complex Gaussian process.

Complex alpha-stable laws are used to model clutters with even heavier impulsiveness and their envelope pdf curves exhibit heavier tails, also shown in Fig. 1. This type of clutters have been reported in many scenarios [5], [6], [8]. It is also found [4] that high resolution sea clutters also have heavier tails than the compound K distribution. A complex symmetric alpha-stable (SaS) process is often described by its characteristic function [7]:

$$\psi(\omega) = \exp\left\{-\gamma|\omega|^{\alpha}\right\} \qquad (2)$$

where $|\omega| = \sqrt{\omega_1^2 + \omega_2^2}$. The parameter $0 < \alpha \leq 2$ is the characteristic exponent directly related with the heaviness of the pdf tail, and $\gamma > 0$ is the dispersion controlling the spread of the distribution similar like the variance of the gaussian distribution. When $\alpha = 2$, the symmetrical alpha-stable distribution becomes the Gaussian distribution.

To combat heavy-tailed non-Gaussian clutters, a fractionally lower-order moments (FLOM) adaptive algorithm has

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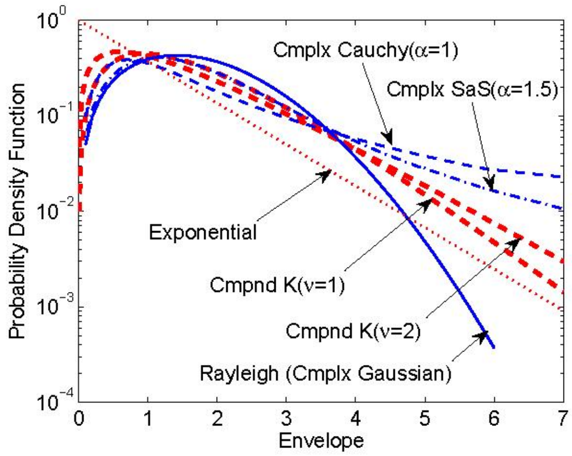


Fig. 1. PDF of the complex envelop of alpha-stable versus the compound K distribution.

been proposed in [10] for space-time adaptive processing (STAP). The FLOM algorithm differs from the commonly used Minimum Variance distortionless Response (MVDR) beamformers in that it minimizes the p-th order moment $(0 < p \leq 2)$ of the output signal rather than its variance. It has been shown that the FLOM algorithm performs better than the conventional MVDR processors in heavy-tailed clutter environments. However, the standard FLOM algorithm suffers from the difficulty of noise amplification similar to the standard Least Mean Square (LMS) algorithm. Besides, there was no guideline for choosing the step size that ensures the convergence.

In this paper, we reformulate the original FLOM algorithm into a normalized FLOM (N-FLOM) algorithm. The normalization is also based on the p-th order moments of the input vector rather than its power. The NLMS algorithm is a special case of the N-FLOM algorithm when setting $p = 2$. The convergence property of the N-FLOM algorithm is investigated and conditions for selecting step size are provided.

The N-FLOM algorithm is also extensively evaluated under Gaussian and SaS clutters for its beampatterns, signal-to-interference-and-noise-ratio (SINR), and target detection performance. The results show that, as the order p decreases, the convergence rate of the N-FLOM improves at the expense of increased residual errors. The N-FLOM or standard FLOM algorithms provide better SINR gains than the NLMS or MVDR processors. When the dispersion of the SaS clutters/noises are small, better target detection performances are also achieved by the N-FLOM algorithm followed by a linear Matched Filter (MF) detector. However, when the dispersion of the heavy-tailed clutters/noises are similar to the target signal power, the N-FLOM or FLOM algorithm combined with linear MF detectors does not provide significant improvement on the detection performance in the low false alarm region. We note that, under heavy-tailed non-Gaussian clutters, nonlinear detectors are more effective, especially in the low false alarm region.

II. STAP and Conventional Beamforming

Consider an arbitrary radar array antenna consisting of M elements with the m-th element located at $\mathbf{x}_m = (r_m, \theta_m, \phi_m)$ in a spherical coordinate system, where r_m, θ_m and ϕ_m denote the radial distance, azimuth angle, and elevation angle, respectively. The radar transmits coherent bursts of K pulses at a constant pulse repetition frequency (PRF) $f_r = 1/T_r$, where T_r is the pulse repetition interval (PRI). Radar returns are collected over a coherent processing interval (CPI) of length KT_r. Within each PRI, there are L time (range) samples collected to cover the range interval. This multidimensional data set can be visualized as a $M \times K \times L$ cube of complex samples [1]. Each sample is denoted $u_{l,k,m}(t)$, for $l = 1, 2, \cdots, L$, $k = 1, 2, \cdots, K$, and $M = 1, 2, \cdots, M$, and t is the sampling time index. The data at a certain range bin l corresponds to a slice of $M \times K$ space-time CPI samples.

Let $N = M \times K$ and denote $\mathbf{U}_l(t)$ the $N \times 1$ concatenated space-time sample vector at range bin l. We have

$$\mathbf{U}_l(t) = [\mathbf{u}_{l,1}^T(t), \cdots, \mathbf{u}_{l,k}^T(t), \cdots, \mathbf{u}_{l,K}^T(t)]^T, \quad (3)$$

$$\mathbf{u}_{l,k}(t) = [u_{l,k,1}(t), u_{l,k,2}(t), \cdots, u_{l,k,M}(t)]^T, \quad (4)$$

where superscript T denotes transpose and $\mathbf{u}_{l,k}(t)$ is the received sample vector at the antenna array. For notational convenience, we drop the subscript l with the understanding that the STAP is performed for the space-slow-time domain.

The radar return vector $\mathbf{U}(t)$ is a mixture of the target echo ($\mathbf{U}_s$) with the uncorrelated interference or jammers ($\mathbf{U}_J$), uncorrelated clutters ($\mathbf{U}_c$), and white background noises ($\mathbf{U}_n$):

$$\begin{aligned}
\mathbf{U}(t) &= \mathbf{U}_s(t) + \mathbf{U}_J(t) + \mathbf{U}_c(t) + \mathbf{U}_n(t), \quad (5)\\
\mathbf{U}_s(t) &= S(t)\mathbf{b}(\omega_s) \otimes \mathbf{a}(\mathbf{\Theta}_s),\\
\mathbf{U}_J(t) &= \sum_{i=1}^{N_J} S_{Ji}\mathbf{g}_{Ji} \otimes \mathbf{a}(\mathbf{\Theta}_{Ji})\\
\mathbf{U}_c(t) &= \sum_{i=1}^{N_c} S_{ci}\mathbf{b}(\omega_{ci}) \otimes \mathbf{a}(\mathbf{\Theta}_{ci}).
\end{aligned}$$

where the point target $S(t)$ is at location $\mathbf{\Theta}_s = (r_s, \theta_s, \phi_s)$ and with Doppler frequency f_0. And $\mathbf{b}(\omega_s) = [1, \cdots, e^{jk\omega_s}, \cdots, e^{j(K-1)\omega_s}]^T$ is the temporal steering vector at the normalized Doppler frequency $\omega_s = 2\pi f_s/f_r$, while $\mathbf{a}(\mathbf{\Theta}_s) = \left[1, e^{j\Omega(\tau_{2s}-\tau_{1s})}, \cdots, e^{j\Omega(\tau_{Ms}-\tau_{1s})}\right]^T$ is the spatial steering vector for location $\mathbf{\Theta}_s$. The operator $\otimes$ denotes the Kronecker matrix product, and $\tau_{ms} = |\mathbf{\Theta}_m - \mathbf{\Theta}_s|/c$ is the propagation delay from the signal source to the m-th array element with c being the wave propagation speed, and Ω is the operation frequency. Also assume that there are N_J jammers S_{Ji} at locations $\mathbf{\Theta}_{Ji}$ with amplitude vector $\mathbf{g}_{Ji} = [g_{Ji}(1), \cdots, g_{Ji}(k), \cdots, g_{Ji}(K)]^T$. There are also N_c independent clutter sources uniformly distributed in a circular ring/sphere around the radar platform [1] with the i-th clutter patch located at $\mathbf{\Theta}_{ci}$ and having the normalized Doppler frequency of ω_{ci}. The Doppler frequency of a clutter is proportional to its angular location. The receiver noise $\mathbf{U}_n$ has no structure in time or space, and thus appears as a uniform noise floor throughout the angle-Doppler plane.

The STAP system consists of tapped-delay-lines attached to each antenna element. Let $\mathbf{W}$ be the concatenated weight vector of the STAP processor, then the output of the STAP $y(t)$ can be expressed in matrix form as

$$y(t) = \mathbf{W}^H \mathbf{U}(t),$$

where the superscript $(\cdot)^H$ represents complex conjugate transpose.

For Gaussian clutter and noise environment, the Minimum Variance Distortionless Response(MVDR) method is commonly used for adapting the weight vector $\mathbf{W}$.

$$\min_{\mathbf{W}} E\left\{|y(t)|^2\right\}, \quad \text{subject to} \quad \mathbf{C}^H\mathbf{W} = \mathbf{h}, \tag{6}$$

where $E\left\{|y(t)|^2\right\} = \mathbf{W}^H \mathbf{R}_{\mathrm{uu}} \mathbf{W}$ with $\mathbf{R}_{\mathrm{uu}}$ being the covariance matrix of the concatenated input vector $\mathbf{U}$ and $E\{\cdot\}$ the expectation operator. The matrix $\mathbf{C}$ is the set of linear constraints and $\mathbf{h}$ is the desired response vector. For example, a simple point constraint [11], [12] may be chosen as $\mathbf{C} = \mathbf{b}(\omega_s) \otimes \mathbf{a}(\mathbf{\Theta}_s)$ and $\mathbf{h} = 1$, which enforces a unit gain response at the target location $\mathbf{\Theta}_s$ and the Doppler frequency f_s. The optimal solution to the constrained minimization problem is well-known assuming that the covariance matrix $\mathbf{R}_{\mathrm{uu}}$ has full rank:

$$\mathbf{W}_{opt} = (\mathbf{C}^H \mathbf{R}_{\mathrm{uu}}^{-1} \mathbf{C})^{-1} \mathbf{R}_{\mathrm{uu}}^{-1} \mathbf{C} \mathbf{h} \tag{7}$$

Direct implementation of (7) requires the knowledge of the covariance matrix of the array input vector. Alternatively, the optimal weight vector $\mathbf{W}_{opt}$ can be decomposed into two orthogonal components: a fixed beamformer $\mathbf{W}_q$ and an unconstrained adaptive weight vector $\mathbf{W}_a$. They are determined by

$$\mathbf{W}_q = \mathbf{C}(\mathbf{C}^H \mathbf{C})^{-1} \mathbf{h}, \tag{8}$$

$$\mathbf{W}_a^{opt} = (\mathbf{C}_a^H \mathbf{R}_{\mathrm{uu}} \mathbf{C}_a)^{-1} \mathbf{C}_a^H \mathbf{R}_{\mathrm{uu}} \mathbf{W}_q, \tag{9}$$

where $\mathbf{C}_a$ is termed the signal blocking matrix. It is orthogonal to $\mathbf{C}$ satisfying $\mathbf{C}^H \mathbf{C}_a = \mathbf{0}$. This decomposition is known as the Generalized Sidelobe Canceller (GSC) and $\mathbf{W}_a$ can be iteratively adapted by the Normalized Least Mean Square (NLMS) algorithm as

$$\mathbf{W}_a(t+1) = \mathbf{W}_a(t) + \mu_a \frac{\mathbf{x}(t) e^*(t)}{\mathbf{x}^H(t)\mathbf{x}(t)}, \tag{10}$$

where $\mathbf{x}(t) = \mathbf{C}_{\mathrm{a}}^H \mathbf{U}(t)$, $e(t)$ is the error signal defined by $e(t) = [\mathbf{W}_q - \mathbf{C}_a \mathbf{W}_a]^H \mathbf{U}(t)$, and t is the index of iteration. The step size μ_a controls the rate of change of the weight vector and $0 < \mu_a < 2$ guarantees the convergence when the algorithm is normalized by the sample covariance $\mathbf{x}^H(t)\mathbf{x}(t)$ in (10).

III. The Normalized Fractionally Lower-Order Moment (N-FLOM) Algorithm

In severe, impulsive clutter and noise environments, the conventional STAP suffers from performance loss due to the fact that the sample covariance are often very large. A fractionally lower-order moment (FLOM) algorithm is to minimize the p-th order moment rather than the variance of the STAP output [7]

$$\min_{\mathbf{W}} E\left\{|y(t)|^p\right\}, \quad \text{subject to} \quad \mathbf{C}^H\mathbf{W} = \mathbf{h}, \tag{11}$$

There is no closed-form solution for the optimal coefficients that minimizes the cost function. When $1 < p < \alpha$, the cost function is convex and a gradient descent method has been proposed [7], [10] to solve for the coefficients as

$$\begin{aligned} \mathbf{W}(0) &= \mathbf{W}_q = \mathbf{C}(\mathbf{C}^H\mathbf{C})^{-1}\mathbf{h}, \\ \mathbf{B} &= \mathbf{I} - \mathbf{C}[\mathbf{C}^H\mathbf{C}]^{-1}\mathbf{C}^H, \\ \mathbf{W}(t+1) &= \mathbf{B}\big[\mathbf{W}(t) + \mu |y(t)|^{p-2} y^*(t) \mathbf{U}(t)\big] + \mathbf{W}_q \end{aligned} \tag{12}$$

Similar to the standard form of LMS algorithm, the FLOM algorithm described by (12) experiences the difficulty of gradient noise amplification when the input signals are large. Besides, the standard FLOM algorithm is difficulty to identify suitable step size μ that can guarantee the convergence. To overcome these problems, we propose a Normalized Fractionally-Lower Order Moment (N-FLOM) algorithm

$$\mathbf{W}(t+1) = \mathbf{B}\left[\mathbf{W}(t) + \mu \frac{|y(t)|^{p-2} y^*(t) \mathbf{U}(t)}{\sum_i |u_i(t)|^p}\right] + \mathbf{W}_q \tag{13}$$

where $u_i(t)$ are the elements of $\mathbf{U}(t)$.

In the GSC implementation of STAP, the proposed N-FLOM algorithm can be expressed as

$$\begin{aligned} \mathbf{W}_a(0) &= 0, \\ \mathbf{W}_a(t+1) &= \mathbf{W}_a(t) + \mu_a \frac{|e(t)|^{p-2} e^*(t) \mathbf{x}(t)}{\sum_i |x_i(t)|^p}. \end{aligned} \tag{14}$$

where $x_i(t)$ are the elements of $\mathbf{x}(t)$.

Note that the N-FLOM algorithm reduces to the NLMS algorithm when $p = 2$. Theoretical analysis of the convergence property for a fractional p is difficult because of no closed-form solutions of the optimum coefficients. We conduct numerical analysis and find that the N-FLOM algorithm is guaranteed to converge if $0 < \mu < p$. We also find that the smaller the order p, the faster the convergence rate and the higher the residual errors. These are demonstrated in the examples in the next section.

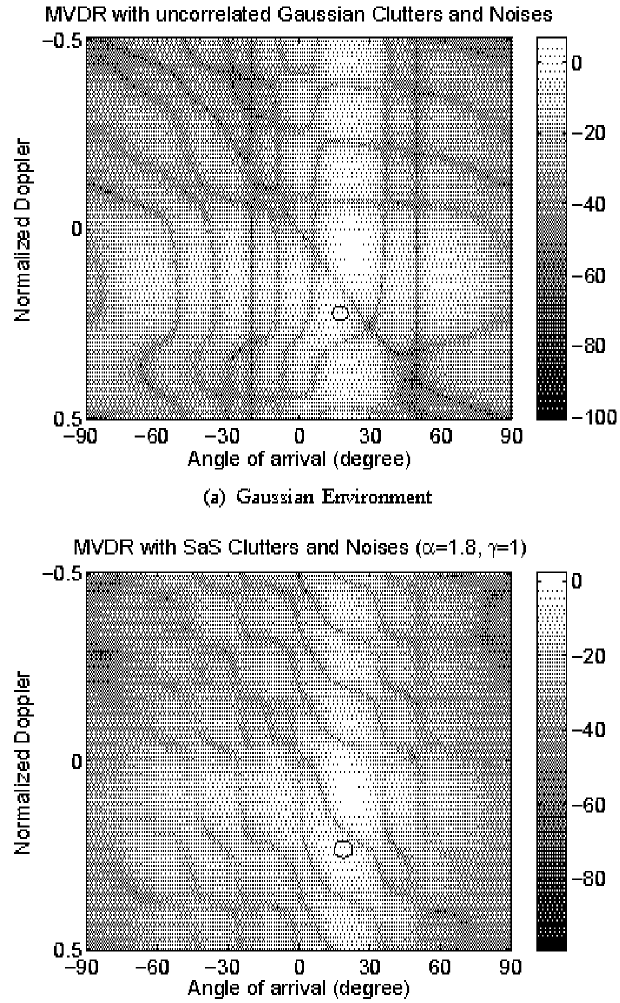
IV. Performance Evaluation

A linear phased array is used to demonstrate the performances of the proposed N-FLOM algorithm. The array consists of 10 equally spaced elements at half wavelength of the operation frequency. The coherent pulse interval is CPI=7. The target signal has a power of 0 dB and is located at angle of arrival (AoA) 20° with a normalized Doppler frequency of 0.25. The noises are independent among antenna elements and CPI taps. It is assumed to be Gaussian or alpha-stable with 0 dB power or dispersion. There are two wideband jammers at AoA of -20° and $+50^\circ$, respectively. Each jammer has full Doppler spectrum and with 15 dB power. There are many clutters at the same range bin from different AoAs. The AoA of the clutters is a random variable uniformly distributed between -180° and 180°. The Doppler frequencies of the clutters depend on their AoAs. The clutters may also be Gaussian or alpha-stable with total power (or dispersion) of 30 dB.

First, the beampattern of the STAP is evaluated, which is defined by

$$\Psi(\Theta, f_d) = |W_{opt}^H \mathbf{b}(f_d) \otimes \mathbf{a}(\Theta)|^2 \qquad (15)$$

The beampatterns of the conventional MVDR processor are evaluated under Gaussian and alpha-stable environments and are plotted in Fig. 2. The location of the target is indicated by the small circle on the angle-Doppler plane at $f_d = 0.25$ and $AoA = 20^\circ$. When the noise and clutters are Gaussian, the MVDR processor can effectively suppress the clutters and jammers by placing deep nulls at jammer location and clutter ridge, as shown in Fig. 2(a). In contrast, when the clutters and noises are heavy-tailed non-Gaussian, the MVDR processor can neither maintain deep nulls at the jammer locations nor suppress the entire clutter ridge, as shown in Fig. 2(b). This is because the conventional MDVR processor uses too many degrees of freedom on the few outliers in the non-Gaussian clutter/noise samples thus sacrifices performance elsewhere.



(a) Gaussian Environment

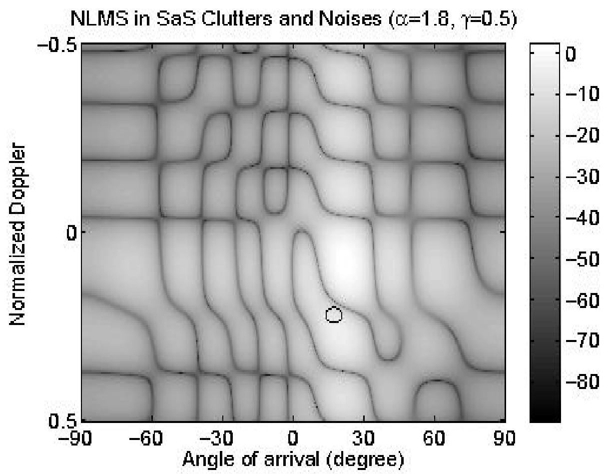
(b) Non-Gaussian Environment

Fig. 2. Beampatterns of the MVDR STAP in Gaussian/non-Gaussian clutters and noises.

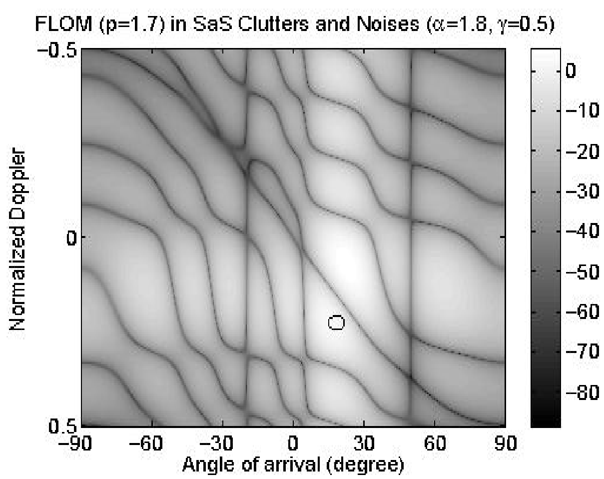
The conventional iterative NLMS algorithm also exhibits performance loss under non-Gaussian clutter environments, as shown in Fig. 3(a). When the outlier samples of the non-Gaussian clutter/noise occurs, the NLMS also loses the ability to suppress jammers resulting in high interference power leaking to the STAP output. The proposed N-FLOM algorithm place less weights on the non-Gaussian clutters thus maintains deep nulls at jammer locations and clutter ridge, as shown in Fig. 3(b). The converged output of N-FLOM has 3 dB higher SINR than that of the NLMS algorithm.

The convergence of the NLMS and N-FLOM algorithms are plotted in Fig. 4. With the same step size, the NLMS algorithm converges much slower than the N-FLOM algorithm in both Gaussian and non-Gaussian environments, as shown in Fig. 4(a). The smaller the order p in the N-FLOM, the faster the convergence. But the smaller the p, the higher the residue errors. Large spikes in the tails of the convergence curves in Fig. 4(b) indicate that outliers occur at those time indexes. The N-FLOM with a smaller p exhibits smaller spikes indicating better robustness against outliers.

The converged outputs of the NLMS and N-FLOM algorithms are fed to target detectors for further evaluation of their detection performances. When a linear matched filter detector is used, the region of operation curves in Fig. 5 plots the probability of detection (P_D) versus the probability of false alarm (P_{FA}) for both Gaussian and alpha-stable clutter environments. In Gaussian clutters, the NLMS and N-FLOM with $p = 1.7$ provide similar performance as the optimal MVDR processor. The N-FLOM with $p = 1$ suffers significant detection loss due to its high residual errors. In the heavy-tailed non-Gaussian environment, the ROC curves degrade significantly for all algorithms, especially at low false alarm rate $P_{FA} < 10^{-1}$. The N-FLOM algorithm

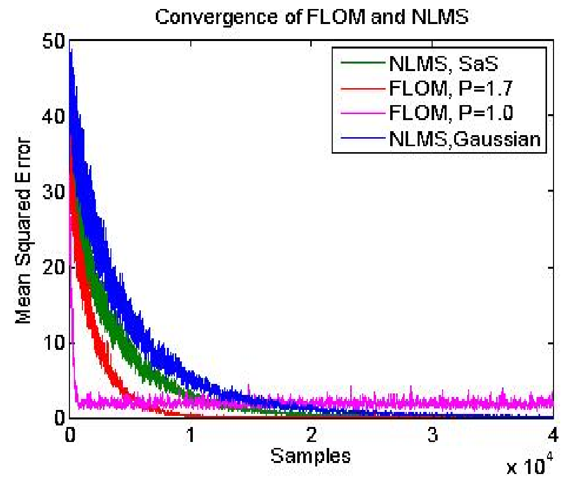


(a) NLMS Algorithm

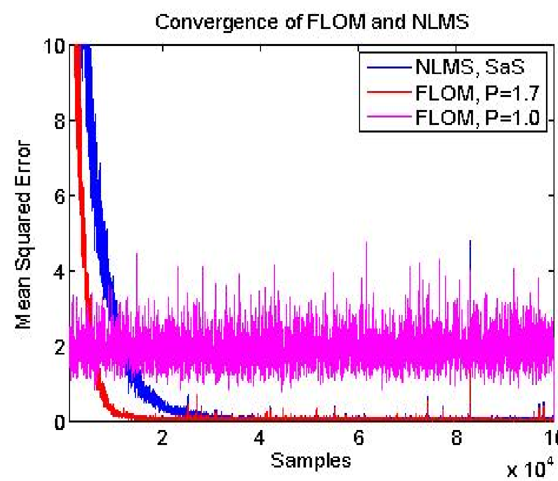


(b) NFLOM Algorithm

Fig. 3. Beampatterns of the iterative STAP in non-Gaussian clutters and noises.



(a) Convergence in non-Gaussian env.



(b) Tail of convergence curve

Fig. 4. Convergence curves of the N-FLOM algorithm compared with the NLMS algorithm.

essentially performs the same as the NLMS algorithm. This is because the number of outliers leaked into the outputs of the two algorithms are more or less the same even though the amplitudes of them may be different. But they all cause significantly high false alarm rate at low input SNR. The MVDR and N-FLOM with $p = 1.0$ perform even worse due to higher interference in their outputs.

What if the output SINR of the STAP is higher? The linear MF detector still performs poorly in low false alarm regions under heavy-tailed non-Gaussian environments, as show in Fig. 6. The higher the SINR at the detector input, the steeper the drop of the detection rate in low false alarm regions. On the other hand, if nonlinear detectors are used, such as hole puncher or hard clipper [7], then the performance is much better than linear detectors, as shown in Fig. 7

This means that the linear detector inherently suffers significant performance loss in heavy-tailed clutters. The FLOM type of algorithms only provide very limited improvement on target detection. Non-linear detectors are more effective for heavy-tailed clutter environments.

V. Conclusion

A normalized FLOM adaptive algorithm has been investigated for space-time adaptive processing (STAP) of phased array radar systems. The algorithm differs from the commonly used NLMS algorithm in that the weight adaptation is proportional to the p-order moment of the error rather than the mean squared error. The normalization is also based on the p-th order moments of the input vector rather than its power. The NLMS algorithm is a special case of the N-FLOM algorithm when $p = 2$.

The N-FLOM algorithm has been extensively evaluated for its beampatterns, convergence rate, and target detection performance. The results have shown that the convergence

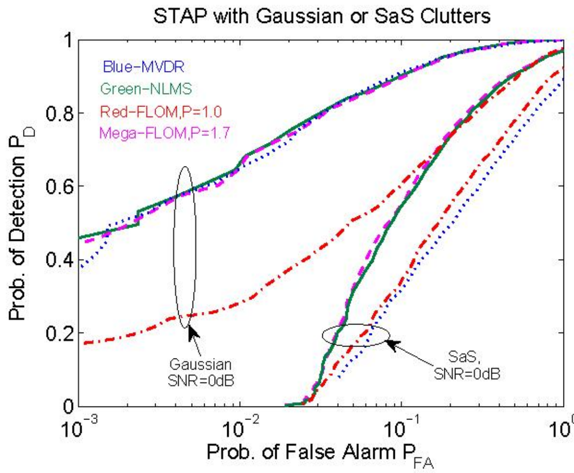


Fig. 5. Performance Comparison of the Matched Filter (MF) target detector with different STAP algorithms. The SNR is measured at the input of the STAP. The jammers and clutters are the same as those in Fig. 3

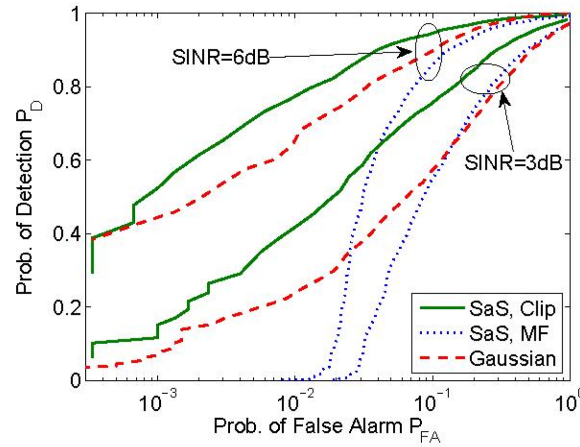


Fig. 7. Performance Comparison of linear and nonlinear target detectors. The SNR are measured at the STAP output or the detector input.

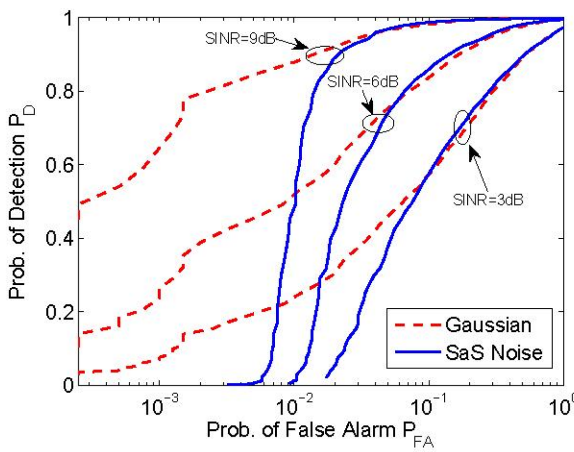


Fig. 6. Region of Operation (ROC) of the linear MF target detector. The SNR are measured at the STAP output or the detector input.

rate of the N-FLOM improves as the order p decreases at the expense of increased residual errors. However, the N-FLOM algorithm provides limited improvement on the detection performance of linear target detectors under heavy-tailed non-Gaussian clutters. Nonlinear detectors are more effective in low false-alarm regions.

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