Mitigation Factors for Multi-domain Resilient Networked Distributed Tessellation Communications

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***Abstract*—Numerous technical calls have converged upon an overarching goal of Resilient Networked Distributed Tessellation Communications (RNDTC) so as to provide long-range communications through the notion of "tessellation" antennas, which are comprised of spatially distributed low Size, Weight, Power, and Cost (SWaP-C) transceiver "polygons." At its core, this approach supplants higher powered amplifiers and large directional antennas with various tessellations of spatially dispersed transceiver polygons. In essence, the transmit power is spatially distributed amongst the polygons, and gain is achieved, via signal processing rather than the use of, by way of example, an antenna aperture so as to concentrate energy. Therefore, signal processing functions enable the various polygons to self-form into an array and enable beamforming, among other techniques, thereby enhancing the desired signals and somewhat obviating intentional/unintentional interference. However, the algorithmic approaches to date have varied pros and cons (e.g., the attainment of reduced sidelobes at the expense of the mainlobe, wherein interference suppression is achieved at the cost of the resolution of the signals). There are promising interference mitigation factor pathways, such as adaptive weight shifting, during the analyzing, transforming, and synthesizing of such signals. However, despite the advantages of adaptive weighting techniques, the computational complexity is extremely high, and the ensuing complexity reduction processes are subject to adversarial exploitation. Accordingly, this paper proposes mitigation factors by way of Artificial Intelligence (AI)-centric Genetic Algorithm (GA) approaches amidst the analysis, transformation, and synthesis amalgam. In particular, preliminary experimental results (to be furthered in future work) indicate promise for the auto-tuning of the Steady State Genetic Algorithm (SSGA) compression factor ζ for more optimal convergence.**

Keywords—Transceiver polygons; Signal processing; Beamforming; Non-permissive cyber electromagnetic environment; 5G networks; Smart grids; Covariance matrix; Spatial filtering algorithms; Convex optimization problems; Semidefinite programming solvers; Space-Time Adaptive Processing; Heuristical vulnerability.

I. Introduction

Traditional long-range communications are achieved by using high-powered Radio Frequency (RF) communications. However, the static RF footprint exposes these long-range oriented communications nodes to adversarial jamming, eavesdropping, and other Advanced Persistent Threat (APT) vectors. This problem is especially compounded amidst an Anti Access/Area Denial (A2/AD) environs. To mitigate against this exposure, the notion of a more agile and Resilient Networked Distributed Tessellation Communications (RNDTC) has been proposed by a variety of agencies and organizations. One of the challenges, among others, is to achieve distributed beamforming without the benefit of apriori information as pertains to the involved constituent nodes. To date, spatial diversity has been assumed and relied upon for clustering purposes. However, practically speaking, as information is obtained in real-time, hitherto heuristically designated single clusters may actually turn out to be comprised of multiple distinct and disparate clusters, and in some cases, the constituent clusters may even represent adversarial organizations (e.g., "blue" units have been engulfed by "green" units, thereby making cluster identification much more complex). Given these nuances of cluster identification, the complexity of interference suppression also greatly increases.

Clearly, operating within contemporary cyber electromagnetic environments necessitates incorporating various Electronic Warfare (EW) countermeasures, and transceiver polygons must contend with interference intrusions amidst a non-permissive environs. The envisioned signal processing (and constituent self-forming array), as construed by many, segues into the promulgation of nulls in the direction of interference so as to effectuate a suppression/mitigation mechanism in the spirit of anti-jamming. Practically speaking, particularly in a battlefield environment, the involved continual relative motion results in a constantly shifting interference direction. To further complicate matters, jamming typically involves dynamic interference source(s). Hence, the null promulgated by a spatial filtering algorithm may not be able to sufficiently suppress the interference. Given the constantly shifting arrival angle of the interference signal and the dynamism involved, computing the pertinent anti-jamming vector from simply a sample covariance matrix derived from a sampled signal, for most cases, proves to be an ineffectual approach vector. This is particularly pertinent in the realm of multi-domain cyber electromagnetic spectrum vulnerabilities for fifth generation (5G) technology standard for cellular networks. Consequently, mitigation factors for the realm of multi-domain RNDTC (e.g., 5G) might be apropos, particularly as several technical calls (e.g., Defense Advanced Research Projects Agency or DARPA) have converged upon an overarching goal of RNDTC so as to provide long-range communications through the notion of tessellation antennas, which are comprised of spatially distributed low Size, Weight, Power, and Cost (SWaP-C) transceiver polygons.

This section introduced the problem space. Section II discusses some of the related work in the literature, the operating environment, such as a potentially contested and non-permissive battlespace, and the state of the challenge. Section III discusses the signal processing intent of various RNDTC initiatives and provides some background information regarding a true adaptive beamforming approach. Section IV discusses the selective updating of the Adaptive Weight Vector

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(AWV), the platform utilized for the involved high-performance Semi-Definite Programming (SDP) solvers, and the strategy for transforming optimization problems to convex form so as to reduce the complexity class from Non-deterministic Polynomial-time Hardness (NP-Hard) to polynomial time, such as for Signal-to-Interference-plus-Noise Ratio (SINR)-related computations. Section V discusses enhancing the maximized SINR, via multi-dimensional Space-Time Adaptive Processing (STAP). Section VI discusses structure exploitation of the covariance interference matrix. Section VII highlights a potential STAP heuristical vulnerability exploitation and posits an experimental mitigation factor for the STAP vulnerability of RNDTC. Section VIII presents some preliminary experimental results. Section IX concludes with some observations, and the acknowledgements close the paper.

II. Related work in the Literature, The Operating Environment, and the State of the Challenge

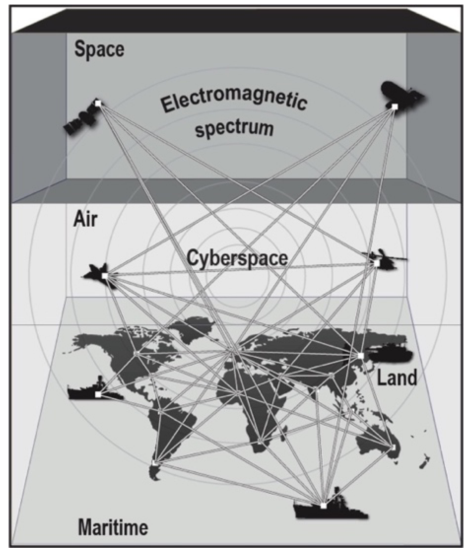
As part of a resilient communications paradigm, particularly for the upcoming 5G paradigm, Ultra Reliable Communication (URC) is construed to constitute a core gauge for performance metrics. The studies available in the corpus of literature tend to examine dependability in the time domain, and only select studies scrutinize dependability in the space domain. Yet, the communications service demand is heterogeneous, non-uniformly distributed, and highly dynamic; axiomatically, the ensuing networks have irregular topologies, and while the majority of the literature focuses upon the adaptation of the network to time-varying conditions, the treatment of the reduction of computational complexity, particularly as pertains to the non-uniformity of the service demand in the spatial domain, has been less prevalent [1].

A. *Related Work in the Literature*

Certain studies in the literature certainly contend with the issue, via a proxy domain (e.g., electrical grid domain), whose Radio Frequency Interference (RFI) and communications performance characteristics are more clearly discernible [2]. The probabilistic availability of URC in such a proxy network are generally analyzed "cell-wise and/or system-wise," and Poisson point process and Voronoi tessellation tend to be utilized in the modeling of the spatial characteristics of cell deployment in both homogeneous and heterogeneous networks [3][4]. By way of example, several approaches involve the notion that for a node n that is a constituent element of a set S, the set of all nodes closer to node n than to any other node of S is the interior of a bounded convex polytope (a special case of a polytope with the property that it is also a convex set contained in the d-dimensional Euclidean space R^d) Voronoi cell for n, and the set of such Voronoi cells is the Voronoi tessellation corresponding to S. This approach, among others, treats resiliency inherently, as it presumes node failures.

B. *The Operating Environment*

To highlight some of the complexities of these networks, among a variety of sources, the U.S. Army Cyber Warfare Field Manual (FM) 3-38 [5], "Cyber Electromagnetic Activities" (supplanted by FM 3-12 "Cyberspace and Electronic Warfare" and others) contends that "Cyber Electromagnetic Activities" encompasses not only the conventional activities involving electronic warfare and spectrum management operations, but also elements of cyberspace operations. The various involved domains of the potentially contested and non-permissive battlespace can be recast as in Figure 1 below.



Source: FM 3-38

Fig. 1. Potential Non-permissive Domains

Accordingly, the envisioned transceiver polygons can be recast for the applications alluded to, among others, in Figure 2 below.

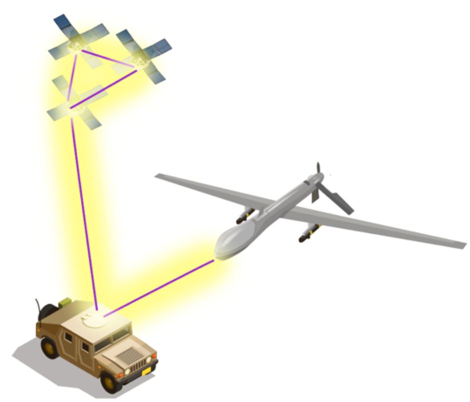


Fig. 2. Potential Transceiver Polygon Applications

The resolution of the challenge for transceiver polygon applications has far-reaching implications for a variety of sectors (e.g., defense, intelligent transportation systems, etc). The cascading effects on the related supply sectors (e.g., semiconductor industry for the implementation of these applications) are quite profound.

C. *The State of the Challenge*

The nature of the challenge centers upon a core need to reduce computational complexity when considering the myriad

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of system parameters interplaying into the achievable link availability. While existing approaches may touch upon complexity reduction processes during the analyzing, transforming, and synthesizing of such signals, to date, they have not robustly addressed adversarial exploitation of the complexity reduction processes. Although some exploration of unbounded polytopes has been conducted, principally, the research has been constrained to that of bounded convex polytopes.

III. The Signal Processing Intent of Resilient Networked Distributed Tessellation Communications (RNDTC) and a True Adaptive Beamforming Approach

Among the core specifications of various transceiver polygon approaches, and temporarily setting aside Size, Weight, Power, and Cost (SWaP-C) considerations, the overall intent is scrutinized. The asserted “Big Idea” for the various transceiver polygon approaches (such as delineated by the Defense Advanced Research Projects Agency or DARPA) center upon the following goal — enhanced robustness against failure/attack and enhanced stealthiness.

A. The Signal Processing Intent of Resilient Networked Distributed Tessellation Communications (RNDTC)

This translates, technically, into the following signal processing tasks, among others, for the approach vector delineated herein (all the following six signal processing tasks should be advanced to Technology Readiness Level or TRL 3+): (1) Advance an adaptive beamforming algorithm that will enhance the beamforming and endeavor to mitigate against interference morphological adjustments, (2) Advance a hybridized Adaptive Weight Vector (AWV) algorithm conjoined with a decomposition-based evolutionary algorithm (a.k.a. Genetic Algorithm or GA), which are both supported by an Artificial Intelligence (AI)-based prioritization algorithm for selective continual updating of the AWV, (3) Advance a Semi-Definite Programming (SDP) algorithm, which can transform the AWV derivation, via maximizing a recast Signal-to-Interference-plus-Noise Ratio (SINR) criterion subject to a similarity constraint, that can be recast as a convex optimization problem, (4) Advance a Quadratically Constrained Quadratic Programming (QCQP) step-down algorithm, which will compute the QCQP special class convex optimization problem in polynomial time, (5) Advance, via a multi-dimensional Space-Time Adaptive Processing (STAP) algorithmic solution set, an enhancement of the maximized SINR, and (6) Advance a structural exploitation of the covariance interference matrix so as to leverage SDP Solvers and ascertain optimal pre-processors.

B. True Adaptive Beamforming Approach

For this discussion, beamforming will refer to the self-forming adaptive array. Axiomatically, the simplistic notion of beam steering (i.e., mechanical positioning to alter the antenna orientation, fixed phase offsets, etc.) will be bypassed, and the discussion shall proceed to true adaptive beamforming. The first priority of an adaptive beamforming algorithm is signal extraction while concurrently suppressing interference as well as noise. The differentiation between the involved methodological approach, as contrasted to conventional approaches (which often experience non-graceful performance degradation) is that of hybridizing, via a prioritization engine, signal-subspace projection (eigenspace-based beamformers, via orthogonal projection of signal subspace, can reduce a substantive portion of noise), diagonal loading (incongruity between the posited and actual array response can be mitigated, via automatic computations), and other methodological approaches to reduce noise, interference, and performance degradation. Collectively, these methods will be selected (based upon the time involved) to enhance the beamforming and endeavor to mitigate against interference morphological adjustments (e.g., propagation channel varying, interference dynamism, etc).

IV. Selective Updating of the Adaptive Weight Vector, a High-Performance Semi-Definite Programming (SDP) Solver, and Reduction from Non-deterministic Polynomial-time Hardness (NP-Hard) to Polynomial Time for Signal-to-Interference-plus-Noise Ratio (SINR) Computations

A particular triumvirate approach has been shown to be effective in prosecuting the task of achieving the described intent: (1) selective updating of the adaptive weight vector, (2) utilizing a high-performance SDP Solver, and (3) reducing the complexity class from NP-Hard to polynomial time for the involved SINR computations.

A. Selective Updating of the Adaptive Weight Vector

Fortunately, the computational availability of Field Programmable Gate Arrays (FPGAs) can facilitate the selective updating of the optimal adaptive weight vector (AWV). Concurrently, derivative null broadening algorithms (the imposition of nulls toward the regions of the nonstationary interference, predicated upon the reconstruction of the interference-plus-noise covariance matrix) offset the need for continuous updating and can move the paradigm towards selective updating. In essence, the AWV can be derived, via maximizing a recast SINR criterion subject to a similarity constraint. On a parallel pathway, the AWV can be validated, and more finely-tuned, via a decomposition-based evolutionary algorithm coupled with AWV, for normalized as well as scaled cases, amidst a multi-faceted non-permissive environs.

B. High-Performance Semi-Definite Programming (SDP) Solver

The described pathways converge for a constrained paradigm, which can be transformed into a convex optimization problem, via SDP solvers. The SDP solvers utilized to date have been implemented on a GNU Octave platform; signal processing and fuzzy logic packages were obtained, via Octave Forge, for use on GNU Octave. As a numerical computation platform, GNU Octave is mostly compatible with the likes of MATLAB. However, as GNU Octave is released under a GNU GPLv3 license, the source code was modified in the lab environment so as to take advantage of Compute Unified Device Architecture (CUDA) multi-threaded parallel

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computing accelerants for the involved SDP solvers to quickly address the various involved convex optimization problems described herein. It should also be noted that GPLv3 avoids the issue of tivoization (the instantiation of a system that incorporates software under the terms of a copyleft software license but leverages hardware restrictions or digital rights management to prevent users from running modified versions of the software on the involved hardware).

C. Reduction from Non-deterministic Polynomial-time Hardness (NP-Hard) to Polynomial Time for Signal-to-Interference-plus-Noise Ratio (SINR) Computations

Once in the convex form, which constitutes a special class, the computational complexity of the involved QCQP can be reduced from Non-deterministic Polynomial-time Hardness (NP-hard) to the desired optimality in polynomial time. Historically, this had been tested in Ilog Cplex Optimizer (a commercial software package for optimization); however, contemporary testing has migrated to AD Model Builder (ADMB) (an open source software package for non-linear statistical modeling) and Interior Point OPTimizer (IPOPT) (a software package for large-scale nonlinear optimization). Preliminary results have delineated maximized SINR for the signal detection processors (amidst interference – including narrowband jamming signals – and noise).

V. ENHANCING THE MAXIMIZED SIGNAL-TO-INTERFERENCE-PLUS-NOISE RATIO (SINR), VIA SPACE-TIME ADAPTIVE PROCESSING (STAP)

Prior experimentation with STAP had been undertaken on the Phased Array System Toolbox. However, the performance of the involved complex simulations, which was essential for subsequent analysis, was suboptimal for the involved cases. As discussed above, preliminary experiments on MATLAB & Simulink segued to a Modified GNU Octave (M-GNU-O) platform. On this customized high performance, multi-threaded platform, certain insights could be quickly gleaned when testing various algorithms with regards to spatial multiplexing. For example, as transceiver polygons were removed, thereby simulating various scenarios (e.g., destroyed transceiver polygons), the array was re-formed and optimal re-configurations were re-computed in quasi-real time; this requisite software-defined paradigm — axiomatic, given the Software-Defined Radio (SDR) rubric of the various transceiver polygon approaches — underscored a fundamental point. If the utilized algorithm and platform exhibited sub-optimal performance, the associated processes would be too immature for subsequent implementation onto a programmable System-on-Chip (SoC) paradigm. Hence, the algorithmic testing on the M-GNU-O proved invaluable.

Indeed, the application of STAP can greatly enhance performance of the posited Resilient Networked Distributed Tessellation Communications (RNDTC) application paradigm, via identification of diversity paths, so as to mitigate against the multipath interference phenomenon as well as more intrusive interference measures. The determination of the diversity paths were formulated, via certain elastic functions. Furthermore, the diversity paths were validated by an AI prioritization engine [6], and exemplar Diversity Paths (DPs) can be seen in Figure 3 below [7].

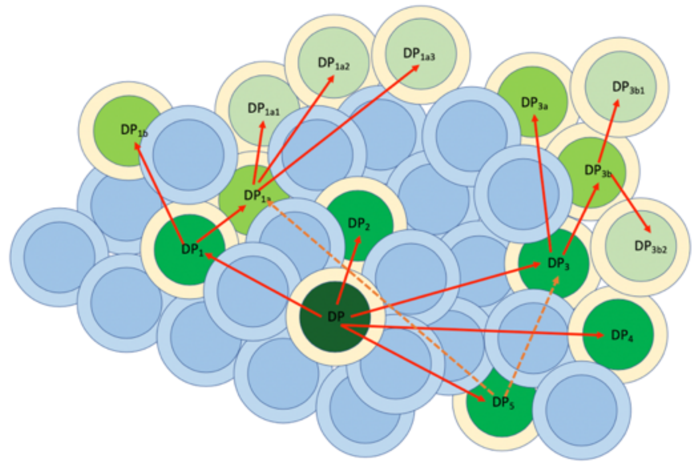

Fig. 3. Exemplar Diversity Paths (DPs)

A key factor to a robust STAP interference suppression paradigm, in addition to an advanced SDR emulation environment platform, resides in the determination of the covariance matrix, and a successful exploitation of the structure of the covariance interference matrix is addressed below.

VI. STRUCTURE EXPLOITATION OF THE COVARIANCE INTERFERENCE MATRIX

A. Pre-Processing

Measurement uncertainty and inaccuracy precludes success by detection processors. Let us take a given signal, which for baselining purposes is construed to be a sequence of infinite duration in the positive and negative directions (i.e., two-sided sequence), of $x = \{x_t, t=0, \pm 1, \pm 2, \ldots\}$ on the time horizon 0, 1, …, N-1 in accordance with (1):

$$y = x_o^{N-1} + \xi \tag{1}$$

where $\xi \sim \mathcal{N}(0, I_N)$ can be representative of simple white Gaussian noise and $z_o^{N-1} = [z_o; \ldots ; z_{N-1}]$; y is utilized to distinguish between two criterion: (1) nuisance noise, wherein $x \in H_0$, and H_0 is comprised of all linear combinations of d_n factors of known frequencies (i.e., the gamut of nuisance noises), and (2) intended signal plus nuisance noise signals, wherein $x \in H_1(\rho)$, and $H_1(\rho)$ is the set of all sequences x representable as s + u with the nuisance noise component u belonging to H_0 and the signal component s equating to at most d_S factors (frequency agnostic), such that the uniform distance, on the time horizon in question, from x to all nuisance noise signals, is at least ρ, such as is shown by (2) [8]:

$$\min_{z \in H_o} || x_o^{N-1} - z_o^{N-1} ||_\infty \geq \rho \tag{2}$$

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The principal goal of the pre-processing algorithm is to distinguish, with a given confidence $1-\alpha$, between (1) and (2) for as small ρ as possible. Given the sample y, a convex optimization problem is solved, and the resultant is compared with a threshold $q_N(\alpha)$, which is a valid upper bound of the $1-\alpha$ quantile of (3) of a given tolerance, as further delineated in (4),

$$||F_N\, \xi||_\infty,\ \alpha \in (0,1) \tag{3}$$

$$\mathrm{Prob}_{\xi\sim N(0,\, I_N)}\{||F_N\, \xi||_\infty > q_N(\alpha)\} \leq \alpha \tag{4}$$

and if Opt (y) <= $q_N(\alpha)$, the nuisance noise pathway is taken and further pre-processing must occur [8]. Conversely, if the nuisance noise has been successfully winnowed, such as shown in Figure 4 below [7], and the signal plus pathway is adopted, then the pre-processing phase advances to an initial processing phase for STAP.

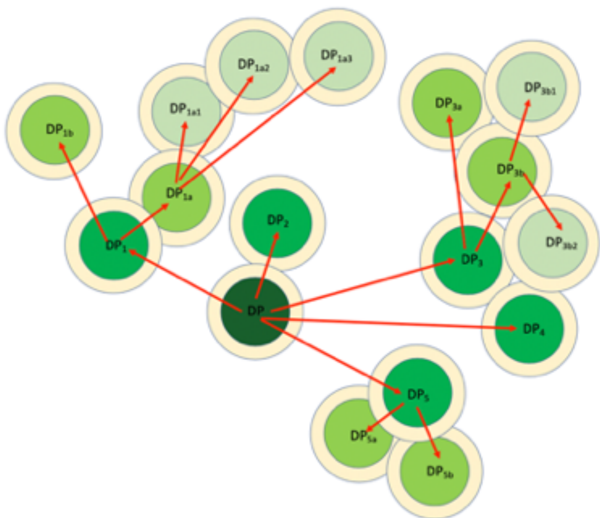

Fig. 4. Nuisance Noise Winnowing for the Diversity Paths (DPs)

It is generally accepted that the optimal STAP filter is often designed based upon being able to discern the known covariance matrix and the known Doppler angle. The principal challenge of STAP is resolving and inverting the unknown interference covariance matrix.

B. *Initial Processing*

Under ideal conditions, given a rescaled matrix, wherein the variables are rescaled, the referenced inversion is numerically stable. Under non-ideal conditions, given an ill-conditioned matrix, the inversion is numerically unstable. Presuming this non-ideal state of varied scaled variables, a viable approach vector would be to have the individual variable scales be kept distinct and disparate from the correlation matrix. Otherwise, the covariance matrix might be adversely impacted with an ill-conditioned number simply because of the varied scaled variables. As an ill-conditioned covariance matrix may amplify estimation error, an ongoing matrix regularization strategy, among other methodologies, is adopted [9].

C. *Ongoing Processing*

The real-time performance of STAP techniques often undergo a non-graceful degradation in heterogeneous environs due to the inaccurate estimation of the interference covariance matrix (R_I) from secondary data [10]; oftentimes, this degradation vulnerability is addressed by endeavoring to suppress the associated noise or clutter. In many cases, the overall STAP effectiveness is determined by the assumed relative homogeneity of the secondary data $\{y_s, s=1, 2, \ldots, N_s\}$, and generally speaking, given the availability of $N_s \geq 2MN$ homogeneous secondary data, the sample covariance matrix $R_s \triangleq (1/\ N_s) \sum_{s=1}^{Ns} y_s y_s^H$ yields a satisfactory estimate of R_I. However, for a fully adaptive STAP, the requisite secondary data constitutes such a large corpus that the associated requisite homogeneity property, amidst the intrinsic non-stationarity of the interference, is acknowledged to be impractical. To overcome such pragmatic constraint limitations, partially adaptive STAP approaches may be employed, which assume that the dominant interferences are constrained to a low-dimensional subspace; various Dimensionality Reduction (DR) STAP algorithms are available, and they are typically classified by the type of pre-processor utilized. By way of example, [beamspace] beamforming (rather than leveraging the spatial statistics of the array elements to differentiate among the signal and interference matrices, the spatial statistics of orthogonal beams — which are formed in different directions — are leveraged; this represents a shift from the higher dimension element space to the lower dimension beamspace while still achieving comparable performance) algorithms typically leverage spatial pre-processing, whereas post-doppler algorithms might leverage temporal [Doppler] pre-processing. In yet other scenarios, the structure of the clutter can be exploited to design pre-processors, which might yield the optimal minimal acceptable rank (i.e., Rank Minimization Problem or RMP) of the clutter covariance matrix [11]; the rank of the clutter covariance matrix provides insight into the expanse of the clutter paradigm as well as indicates the number of Degrees-of-Freedom (DoF) needed to achieve an effective clutter cancellation. In many cases, the involved dimensionality reduction is achieved, via various matrix rank reduction methods (wherein the approximating matrix, the optimization variable, has reduced rank compared to the given matrix, the sourced data), and the resultant lower rank matrix decomposition-based solution necessitates twice the secondary measurements as that of the rank of the clutter covariance matrix so as to achieve optimal STAP performance. In contrast to the rank reduction approach, the spatio-temporal sparsity recovery approach needs a substantially even smaller corpus of secondary data [12].

1) *Rank Reduction Approach*

Generally speaking, matrix decomposition problems involve a sample covariance matrix being decomposed into the sum of a low rank positive semidefinite matrix and a diagonal matrix. This equates to computing $\hat{R}_I = \hat{R}_c + \hat{R}_n$, where $\hat{R}_c$ and $\hat{R}_n$ are examined, via resolving the following Rank Minimization Problem (RMP):

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$$(\hat{R}_c\ , \hat{R}_n) = \arg \min_{R_c, R_n} \ \text{rank}\ (\hat{R}_c), \quad (5)$$

$$\text{subject to} \begin{cases} R_c + R_n = R_s \\ R_c \geq 0 \\ R_n \text{ diagonal} \end{cases}$$

The RMP cannot be solved directly as the rank function is nonconvex and discontinuous. Hence, to make the problem convex, the rank function is replaced with the trace function and resolved by treatment as a Trace Minimization Problem (TMP):

$$(\hat{R}_c, \hat{R}_n\ ) = \arg \min_{R_c, R_n} \ \text{tr}\ (\hat{R}_c), \quad (6)$$

$$\text{subject to} \begin{cases} R_c + R_n = R_s \\ R_c \geq 0 \\ R_n \text{ diagonal} \end{cases}$$

Since the rank function tallies the number of nonzero eigenvalues, and the trace function computes the sum of the involved eigenvalues, the equation can be reconstrued as an equivalent SDP:

$$(\hat{R}_c, \hat{R}_n\ ) = \arg \min_{R_c, R_n} \ \text{tr}\ (\hat{R}_c), \quad (7)$$

$$\text{subject to} \begin{cases} \begin{bmatrix} W_1 & R_c \\ R_C^H & W_2 \end{bmatrix} \\ R_c + R_n = Rs \\ Rc \geq 0 \\ R_n \text{ diagonal} \end{cases}$$

Once in this form, there are numerous SDP solvers (e.g., SDPT3, which is a MATLAB/GNU Octave Semi-Definite Programming or SDP software package) available for these types of problems, and as previously discussed in Section IVB, the M-GNU-O platform has readily supported various high-performance SDP solvers.

2) Spatio-Temporal Sparsity Recovery Approach

Generally speaking, the spatio-temporal sparsity recovery approach is analogous to the rank reduction approach; in essence, the involved l_0-minimization problems are Non-deterministic Polynomial-time Hardness (NP-Hard). However, under certain conditions, such as described in Donoho's "Compressed Sensing," convex relaxation methods may be applied, wherein the l_0 norm is replaced by the l_1 norm, thereby maintaining the sparsity while also being a convex function [13][14]. There are numerous convex relaxation methods, and once again, as previously discussed in Section IVB, the M-GNU-O platform has readily supported various high-performance SDP solvers.

D. Post-Processing

As a semblance of analytical scrutinization, by way of post-processing, it is noted that while sidelobe interferences can be sufficiently suppressed by adaptive beamforming, countering interference in the mainlobe area segues to other issues, such as pattern distortion and decreased output signal with regards to the Signal-to-Interference-plus-Noise Ratio(SINR). Among others, various adaptive Kalman filter algorithms have been experimented with for coping with the unknown interference covariance matrix, which can involve [measurement] noise covariance matrices estimation (which is based upon state estimation techniques) [15]; these provide an approximation of the noise in the involved system [16]. In essence, a lower covariance value would segue to higher confidence in the detection result at time *t*, whereas a higher covariance value would segue to a higher confidence in the prior detection result at time *t-1* rather than that of time *t*.

Overall, this Section VI has articulated the leveraging of SDP solvers (and the further leveraging of optimal pre-processors). As discussed, the known structure of the clutter can be exploited to design pre-processors, which might facilitate the resolving of the clutter covariance matrix, via RMP. With regards to the known structure of the clutter, in many cases, this can be baselined over time. For example, diplomatic facilities (e.g., embassies) and their associated military annexes are relatively static; acknowledging that there is ongoing construction, renovation, and activities in the abutting areas, the structure of the clutter at relatively static locations can be better discerned with time (i.e., baselining). Accordingly, pertinent hyper-locale pre-processors can be devised.

VII. Space-Time Adaptive Processing (STAP) Heuristical Vulnerability Exploitation and an Experimental Mitigation Factor for the STAP vulnerability of Resilient Networked Distributed Tessellation Communications (RNDTC)

A. STAP Heuristical Vulnerability Exploitation

The described heuristic (lower covariance value → higher confidence in the detection result at time *t;* higher covariance value → higher confidence in the detection result at time *t-1)* constitutes a configuration parameter*,* which can be exploited, particularly when time-sensitive real-time detection systems are central to the system (e.g., You Only Look Once or YOLO v3) and Adversarial Machine Learning (ML) attacks (AMLA) are involved. The AMLA can target from among pre-processing, initial processing, ongoing processing, and post-processing (e.g., manipulation of doppler has already long been an issue [16]). Some would construe this to constitute a long-range, precision non-lethal effect, in accordance with the U.S. Army's "America's Army: Ready Now, Investing in the Future (FY19-21 Accomplishments and Investment Plan)" Multi-Domain Task Forces (MDTFs), which are "tailorable units that join Intelligence, Information, Cyber, Electronic Warfare, and Space (I2CEWS) capabilities with fires and other capabilities to deliver long-range, precision non-lethal, and as appropriate, lethal effects across joint and multi-national platforms." In the described scenario, the "Long-Range Precision Effect" is shown to be potentially operative on the STAP processing of what could be part of a mission-critical communications apparatus (as a target node). A real-world example of the import centers upon is U.S. Secretary Pompeo's announcement on 29 April 2020 that the U.S. Department of State will "require a clean path for all 5G network traffic coming into and out of U.S. diplomatic facilities at home and overseas." The described STAP heuristical vulnerability exploitation is part of that cyber-physical supply chain consideration.

B. Experimental Mitigation Factor for the Space-Time Adaptive Processing (STAP) Vulnerability of Resilient Networked Distributed Tessellation Communications (RNDTC)

The optimal filter is a unique member among an infinite set of consistent filters [17]. The configuration parameter or parameter tuning of the optimal filter, even after it is ascertained, can be manipulated. Tuning typically employs two approaches: Statistical Consistency Tests (SCT) (which employs statistical hypothesis testing to determine the consistency of the filter), and True Covariance Analysis (TCA) (which facilitates a computable true estimation error covariance). However, neither SCT nor TCA seem to suffice for ascertaining the true performance of the filter. Hence, AI-centric automated tuning approaches have been experimented with.

Fundamentally, Genetic Algorithms (GAs) are optimization algorithms. GAs tend to be quite efficient when a large search space is involved, the involved optimization computation can readily be parallelized, and they are of zero order (i.e., independent of the prior). GAs treat each parameter set, within the parameter space, individually. The fitness function for a given individual entity is generated by SCT, and if the individual entity is found to be consistent, its fitness is the estimated covariance norm. Alternatively, the fitness is comprised of the consistency values *J*. This is presented in (6) below [18].

$$\text{fitness} = \begin{cases} \parallel P \parallel & J < 0.05 \\ -J & otherwise \end{cases} \tag{6}$$

The approach utilized was that of a GA subset entitled "Steady-State GA" (SSGA), wherein: (1) if two filters are inconsistent, their fitness value is negative, and the closer one to zero is more optimal; (2) if only one filter is consistent, the fitness value is positive, and it is construed as more optimal than the other inconsistent filter with the negative fitness value; and (3) if both filters are consistent, the more optimal filter is that with the smaller fitness value. Consequently, this re-evaluation of the filter performance enhances the reliability by removing filters that do not perform well in a consistent fashion [18][19]. In essence, the SSGA can be construed as a discrete-time dynamic system non-generational model. The value-added proposition for the experimental mitigation factor for the STAP vulnerability of RNDTC is a compression factor ζ that, in some instances, serves to squeeze the steady-state population towards an accelerated convergence. A larger compression factor ζ is indicative of a compressed convergence and corresponds to a higher magnitude jump size for the fittest proportion from one generation to the successor generator; conversely, a smaller compression factor ζ is indicative of an elongated convergence and corresponds to a lower magnitude jump size. To avoid issues of local minima (e.g., random noise), dynamically turning the compression factor ζ may provide an invaluable methodology to adjust convergence, thereby resulting in a tunable parameter that obviates the problem of premature convergence and non-optimality. In summary, the SSGA approach can indeed effectuate auto-parameter tuning so as to minimize the window for exploitation as pertains to the identified STAP heuristical vulnerability exploitation. The described work was performed in an experimentation-innovation lab in Orlando, Florida; other labs (a.k.a. "living labs") for exploring 5G-enabled defense applications and use cases are starting to emerge and multiply [20].

VIII. PRELIMINARY EXPERIMENTAL RESULTS

Simulations run atop the M-GNU-O platform have indicated that statistical consistency tests are not reliable for discerning an optimal filter. Rather, the tests yield an infinite set of consistent filters within which the optimal filter is a unique member. Preliminary experimental results indicate promise for the auto-tuning of the Steady State Genetic Algorithm (SSGA) compression factor ζ for more optimal convergence of an optimally tuned filter (or a set of near optimally tuned filters). Indeed, auto-tuning is central to this capability, and the compression factor ζ is instrumental in dictating the rate of the steady state towards convergence. Large ζ values may be indicative of earlier (i.e., premature) convergence, thereby segueing to specious solutions that have keyed in on local minima and/or noise, thereby precluding a more optimal convergence. Accordingly, one observation centers around the fact that the ability to re-tune the compression factor ζ to a lower value (i.e., <1) seems to be critical. Another observation centers around the Principal Tuning Result (PTR) for an exponentially bounded fitness, given the characteristic time λ for an overall time dependent population fitness *F*, which satisfies the convergence condition in (7):

$$\text{PTR} = [F_{t+1} - F_t] < F_t\,(e^{-\lambda t} - 1) \tag{7}$$

In essence, the PTR allows for an SSGA optimization estimate for the convergent approach of the time dependent population fitness F in a quasi-analytical fashion prior to a given numerical iteration, and this is consistent with other research in the field, such as that conducted at the Sante Fe Institute [21]. Field experiments were conducted in environments, wherein the involved electrical grids (in these cases, "Smart Grids") were generating Radio Frequency Interference (RFI), via faulty electric equipment, that went beyond the prototypical radiation emissions of the usual powerlines and electric utility-related equipment (classified as "incidental radiators" by the Federal Communications Commission or FCC in the U.S.).

IX. CONCLUSION

In many cases, prototypical weighting techniques are utilized to attain reduced sidelobes at the expense of a more expansive and robust mainlobe [22]. In essence, some interference suppression is achieved by sacrificing the resolution of the signals. For example, the introduction of self-induced white noise (signals that mitigate against/mask other signals) could mitigate adversarial-introduced attack vectors; the white noise is generated, via receiver-based nullification endeavors, wherein the weights and phase shifts associated with a receive node or cluster of receive nodes dynamically adapt in a coalition fashion to create directional nulls. Along the vein of weight shifts, adaptive weighting techniques utilize time-varying weights so as to achieve more robust interference suppression as well as relatively higher resolution signals. Despite the advantages, adaptive techniques are computationally intensive (e.g., matrix inversion), and a variety of processing tasks are required to reduce this computational complexity. At the core, transforming problems into convex optimization problems, which can be resolved in polynomial time, and leveraging SDP solvers is a common thematic. However, the involved processes, such as STAP, reveal heuristical reliances that are subject to adversarial exploitation. Accordingly, these heuristics (i.e., configuration parameters) need to be sufficiently annealed and optimized. Accordingly, this paper proposes mitigation factors by way of AI-centric GA amidst the analysis, transformation, and synthesis amalgam. Section VIIB discussed the SSGA approach to effectuate auto-parameter tuning so as to minimize the window for exploitation as pertains to the identified STAP heuristical vulnerability exploitation. Proxy use cases (e.g., electrical grid sector) proved useful for auto-tuning experimentation as pertains to the compression factor ζ, which dictates the efficacy of the convergence upon an optimally tuned filter (or a set of near optimally tuned filters). Future work will involve furthering the exploration of the SSGA compression factor ζ and conducting more in-depth research into the SDP solver(s) atop the customized M-GNU-O platform.

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