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Recent Trends and Findings in Cognitive Radar

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***Abstract*: We provide an overview of recent advances that have come about in the area of cognitive radar over the past decade. The area of cognitive radar involves closed loop radar operation to overcome the challenges imposed by harsh environments, difficult targets, and a rapidly shrinking spectrum. In particular this construct is devised to bring to bear all available resources on transmit and receive as well as exploit situational awareness of the operational environment to maximize system performance. The multidisciplinary nature of the field is highlighted and salient advances are presented to motivate the interested reader to delve deeper.**

Keywords: Cognitive Radar, Fully Adaptive Radar, Detection, Tracking, Classification, Scheduler, Resource Allocator, Controller

I. INTRODUCTION

Typically, most radars operate in open loop, where a transmit resource generates the probing signal, which illuminates an environment consisting of one or more targets of interest, background clutter, one or more jammers, and background white noise. The returns from the target and the background (collectively referred to as the channel) are processed at a receiver, whose task is to separate the target returns from the background. However, the onerous requirements of concurrent detection, tracking, and classification from single and multiple sensors exacerbated by the challenges posed by harsh environments, hard to detect targets, and a rapidly diminishing EM spectrum necessitate closing the loop in the radar at multiple levels involving the transmit resource, adaptive receiver, tracker, and classifier. Additionally, auxiliary information pertaining to the environment from a plethora of sources can be brought to bear in the front end of the radar signal processor. The resulting construct from such an approach is thus variously known as fully adaptive radar (FAR), closed loop radar, or cognitive radar and is depicted in Figure 1. Application of the principles of cognition for a variety of problems were introduced in a seminal treatise by N. Wiener[1]. Cognitive sciences as a discipline in its own right has enjoyed a rich history (see [2] and references therein for more detail). A tutorial account of this discipline is beyond the scope of this paper. Our focus is instead the application of principles and insights from this area to the radar problems.

It is important to note that the construct of fully adaptive radar has been on the minds of the radar system developers from the inception of radar. However, limitations of hardware and computing power precluded the realization of this construct. Recognizing that radar is an intensely multidisciplinary area, advances in A/D converters, RF circuit design, signal and data processing algorithms, computer hardware and software enable us to envisage realization of the cognitive radar construct for the first time. Precursors to realizing this construct include important advances in the areas of knowledge aided radar signal processing [3,4 and references therein], waveform diversity [5] and MIMO radar [6].

As a consequence, two important perspectives for cognitive radar emerged in the seminal treatises of [7] and [8]. The work of [7] expounds on a knowledge aided approach for cognitive radar bringing to bear a sense-learn-adapt framework to cognitive radar, while [8] devotes much attention to the perception-action cycle inherent to a cognitive dynamic system. Both perspectives are equally valid and one or the other can be brought to bear on the instantiation of cognitive radar for a given application. The work of [9] proposes the use of a waveform diversity approach for cognitive radar based on a biologically inspired paradigm.

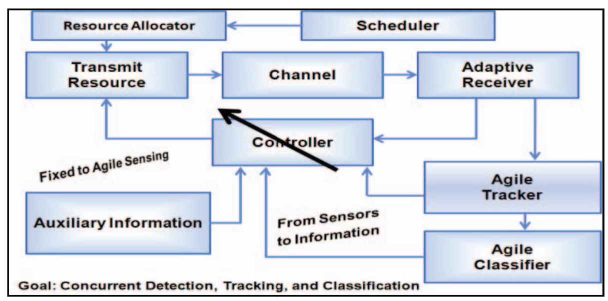

Fig. 1. Fully Adaptive Radar Construct

In the following sections we present an overview of related contributions from several research communities that are active in the area. Limitations of space preclude a more comprehensive listing of relevant citations. Therefore, seminal contributions are cited with the view to encouraging the interested reader to explore in greater detail the references listed therein. It is important to note that the FAR construct depicted in Fig. 1 is applicable for single as well as distributed radar constructs that allow both co-located and widely spaced transmit-receive antennas. Each of these configurations has a specific role in the context of the application at hand.

II. PROBLEM STATEMENT

Fundamental questions that arise with respect to the FAR construct shown in Fig. 1 are: What is the performance limit afforded by FAR? Given the large number of free parameters how close can one get to the performance limit? How much data is needed in order to get to within a prescribed level of the performance limit? How robust is the FAR performance to parameter estimation error and model mismatch? What is the underlying computational cost? These issues must be addressed

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for the case of single as well as distributed radar scenarios featuring co-located transmit-receive antennas as well as widely spaced trans-receive antennas from the standpoint of detection, tracking, and classification. In some environments it becomes necessary to operate strictly in a passive radar mode. In such instances control over the transmit waveform is lost and the focus turns to the issues of illuminator selection and sensing geometry selection for maximizing FAR performance. Consequently, this gives rise to a broad spectrum of research activities spanning theory, systems, and experimentation. The FAR construct is first decomposed into four anchor technical areas of phenomenology, adaptive signal processing on receive, waveform diversity, design, adaptation and MIMO radar and finally exploitation products resulting from FAR. These cornerstone technical areas are inter-connected and exhibit considerable synergy in that advances in any one area tend to aid in FAR performance enhancement. Furthermore, these areas form the fundamental enablers for a number of applications such as airborne radar, space based radar, building penetrating radar, foliage penetrating radar, ground penetrating radar, and cooperative RF/EO sensing. In the subsequent sections we dwell on specific advances pertaining to these areas that enable performance characterization for the FAR construct from a detection and tracking perspective. We also devote attention to key principles and concepts that permit us to carry out the analysis.

III. Adaptive Detection

The problem of space-time adaptive processing (STAP) for radar requires the formation and inversion of the interference covariance matrix. Covariance matrix estimation needs a large amount of representative target-free training data. Furthermore, the computational cost of matrix inversion grows exponentially with increasing dimension. The availability of representative training data also comes into question in the face of a fiercely heterogeneous environment as well as due to systems consideration such as bandwidth. Consequently a number of approaches have been developed in the literature to address this problem (see chapters 4-7 in [3] for a partial list of the relevant literature). An important open problem in this context is one of covariance matrix with structure and rank constraints. This problem was addressed in a recent paper [10]. The role of convex optimization for adaptive radar was highlighted in this paper, which developed a closed form solution to a non-convex problem using relaxation. Performance analysis of the technique was carried out using data from the DARPA KASSPER program (Chapter 4 in [3]) and compared with other candidate techniques. The rank constrained maximum likelihood (RCML) estimator developed in [10] outperformed all competing methods. A performance comparison in terms of output signal-to-interference-plus-noise-ratio (SINR) of the adaptive matched filter for detecting a rank one signal in interference composed of clutter and noise is shown in Fig. 2. The plot shows the output SINR as a function of angle and Doppler using KASSPER dataset 1 for the sample matrix inverter (SMI), fast maximum likelihood (FML), RCML, Eigen canceller (EigC) and leave out one (LOOC). The result reveals that the RCML provided unbeatable performance given the constraints of interference structure and clutter subspace rank. Extension of the approach to handle the case of Toeplitz symmetric covariance matrices with structure and rank constraint was carried out in [11] with proven success. The results of [11] show that the algorithm developed therein outperformed all competing methods for this problem. These efforts revealed the potential of convex optimization techniques for adaptive radar and set the stage for a broader set of investigation pertaining to joint adaptive processing on transmit and receive as well as SINR performance prediction employing constrained radar waveform design, which are discussed subsequently.

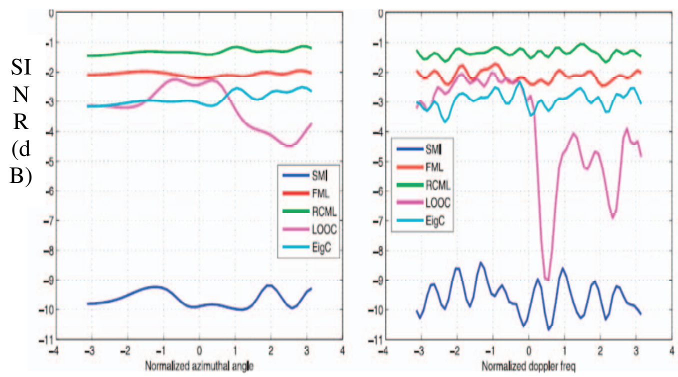

Fig. 2. SINR Performance of candidate radar STAP algorithms using KASSPER Data: Spatio-temporal dimensionality=352 Number of Training data snapshots=300

IV. Joint TX-RX Adaptive Processing

A fundamental problem for cognitive radar is one of joint adaptation of the transmit waveform and receive filter weight vector to maximize SINR performance [7]. This problem was considered for radar STAP in [12] from the standpoint of introducing waveform dependence to lower the error variance at the output of the minimum variance distortionless response (MVDR) beamformer. In traditional receive only MVDR beamforming, the transmit waveform remains fixed. Consequently, the covariance matrix on receive remains unchanged from one coherent processing interval (CPI) to the next. However as exposited in [12], when the transmit waveform is changed on a pulse-by-pulse basis or CPI by CPI basis, the covariance matrix varies accordingly. Consequently, the minimum eigenvector solution that holds for traditional MVDR beamforming with a quadratic weight vector constraint is no longer applicable. Instead the SINR maximization problem at the MVDR beamformer output now becomes a highly non-convex problem. This issue is exacerbated by the fact that the receive weight vector calculation is a function of the transmit waveform and optimizing the transmit waveform involves a matrix, which is a function of the receive weight vector. This coupled problem does not admit to a simple analytically tractable solution.

However, the joint adaptive processing problem allows decomposition into 2 sub problems that are individually convex as shown in [12]. Principles of convex optimization can then be brought to bear in the framework of alternating minimization to develop an iterative computational solution. The issues of convergence speed, computational cost, and training data support for covariance matrix estimation, non-negative definiteness of the covariance matrix on receive and its analog in the waveform domain are addressed in a systematic manner in [12]. This sets the stage for generalization to the distributed radar problem. The non-convex nature of the objective function is illustrated in the result of Fig.3 where the convergence with number of iterations changes from one trial to another. A formal proof of the non-convexity will be reported in a future publication.

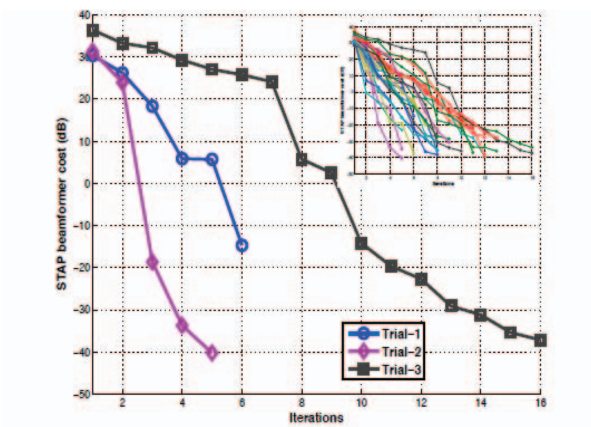

Fig. 3: Non-convexity of overall objective function

Another important direction pursued in this context is the issue of SINR performance prediction using constrained radar waveform design. The problem involves minimization of a non-negative definite quadratic form. In the absence of any constraints on the waveform except for finite energy, the resulting solution is the previously mentioned minimum eigenvector solution. In particular, system constraints preclude the use of the minimum eigenvector solution for the radar waveform. Imposing constraints such as cumulative modulus and peak-to-average-power-ratio (PAPR) complicates the waveform design considerably. While the cumulative modulus constraint is convex, the same cannot be said of the PAPR constraint. This problem is addressed in [13] by representing the desired waveform as a linear combination of the sub-dominant eigenvectors of the interference covariance matrix. It is important to note here that basis selection is non-unique and thus precludes us from making any optimality claims. A key result to note here is that as the constraints on the waveform are tightened, more basis vectors to represent the signal are called for. Consequently, SINR performance is degraded as shown in Fig. 4. Other basis selection techniques to address this problem are currently under investigation. Broadly these can be classified as signal dependent basis selection and signal independent basis selection. Performance of these techniques will be reported in a future publication.

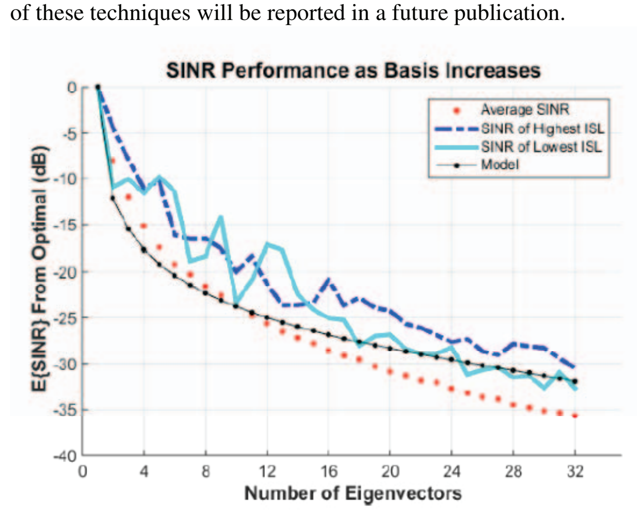

Fig. 4: SINR Performance vs Number of Eigenvectors

In many instances it becomes imperative to operate in a passive radar mode, where there is no control over the radar waveform. In these instances the issues of illuminator selection and sensor placement geometry are crucial for maintaining acceptable performance. In this context, performance bounds for delay Doppler estimation were developed in [14]. In a related paper [15] developed the ambiguity function analysis for illuminators of opportunity, which may be readily available. These advances enable determination of the performance limit attainable for a given scenario. In turn this allows illuminator selection, which has most favorable ambiguity function properties, and guides the placement of sensors to maximize performance. Recognizing the fact that a perfect reference signal for passive radar is not typically available in practice, no optimality claims can be made on the performance of the cross correlation detector. In [16] principles of random matrix theory were applied to the passive radar detection problem to improve upon the performance of the cross correlation receiver for this problem. A novel contribution in [17] develops for the first time for radar a commonly used technique from multiple antenna communications, which relies upon a probative MIMO mode for channel estimation. A key contribution herein is the reduction of the covariance matrix estimation for adaptive radar into a system identification problem. This remarkable result has important implications in terms of training data support for covariance matrix estimation and the resulting computational cost.

V. COGNITIVE RADAR TRACKING

The research in [18] developed a general cognitive sensor/processor framework that can be applied to a variety of system objectives, or tasks. The basic framework consists of four components: the scene (target and environment), sensor, processor, and controller. The framework includes the feedback mechanism and optimization criterion used to obtain the next set of sensor data to optimize the performance of the processor. The framework was then specialized for the task of single target tracking. Additionally, [18] developed the tracking framework by partitioning the processor into a detector and a tracker, allowing feedback from the tracker to perform guided detection. This is a key feature of the framework that allows cognitive control of both the sensor and processor for improved performance as shown in Fig. 5

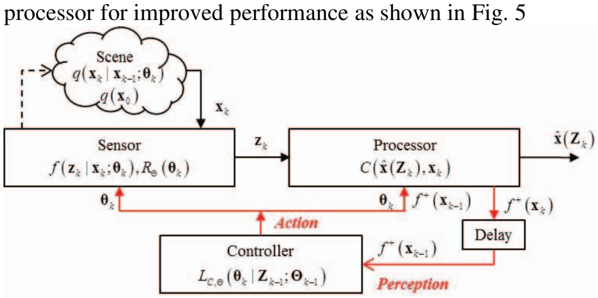

Fig. 5: Closed Loop Radar Tracking Framework

The framework is based on the *perception-action cycle* and includes *sensing* in the transmitter and receiver; *processing* in the detector and tracker; *perception* in the conversion of sensor data to the posterior density of the state vector; *memory* of all the past data in the posterior density; *attention* in the penalty function of the guided adaptive detector, which focuses the detector on the relevant region of the detection surface; *prediction* in the Predicted Conditional Bayesian Information Matrix (PC-BIM), which predicts the performance of the next measurement; and *decision-making* in the controller, which decides on the next values for the sensor parameters based on the predicted performance. Experimental results based on this construct are reported in a companion paper. Complementary advances to the research described in this theme include the radar resource manager as exposited in [19] and [20]. In particular, the results of [20] were validated using measured data from experiment to demonstrate the savings in radar dwell time for non-coherent integration, where the target was modeled as a convex combination of Swerling models. A similar body of literature exists for the problem of radar imaging using cognitive techniques. A comprehensive listing of these approaches is beyond the scope of this treatise.

VI. CONCLUSIONS

This paper contains an overview of recent advances in the emerging area of cognitive and fully adaptive radar. The focus of this effort has been largely the detection and tracking functions in a cognitive framework. The role of enabling techniques from convex optimization and random matrix were briefly discussed. Open problems in the field are outlined. Limitations of space precluded a more comprehensive list of references. However, the interested reader is encouraged to delve deeper into the citations contained in the references herein.

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