EXPLOITATION OF SIGNAL STRUCTURE IN ARRAY-BASED BLIND COPY AND COPY-AIDED DF SYSTEMS

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ABSTRACT

A general approach to array-based blind copy and copy-aided DF of structured communication signals is presented that can substantially outperform conventional techniques, by exploiting additional information about the *structure* of the signals of interest to the reception system. The techniques are derived from optimal parameter estimation concepts that directly incorporate this additional information into the waveform or parameter estimation strategy. The resultant algorithms demonstrate strong theoretical, experimental, and implementation advantages over conventional techniques. Results are demonstrated for blind separation and copy-aided DF of co-channel FM, CPFSK, DSB-AM, and burst waveforms.

1. INTRODUCTION

The problem of detecting, copying, and localizing communication signals in dense interference environments is of increasing importance to the defense community. The expansion of commercial and military broadcast, communications, and radar systems in the microwave bands has resulted in severe spectral crowding over many frequencies. At the same time, restrictions placed on modern signal collection systems typically requires collection of signals over broad geographical areas. As a consequence, these systems must operate in environments containing large numbers of unknown time and frequency coincident signals of interest (SOIs), as well as strong deliberate and inadvertent interference.

Multielement antenna arrays have the potential to overcome this problem, by exploiting the differing *spatial coherence* of the signals impinging on the array due to the wavefronts arriving at distinct directions of arrival (DOAs).

In many applications, the number of antennas required to separate the signals can be quite low, for example, M antennas are typically sufficient to separate M overlapping SOIs, if the SOIs are received at a sufficiently high power above the interference in the channel.

Serious challenges still exist, however, with implementation of array-based signal collection systems. The numbers, strengths and DOAs of the signals received by such systems are typically unknown and time-varying over the collect interval. Furthermore, the system must use *blind* techniques that do not rely on the content of the SOIs to adapt the array, since this information is typically not available to the collection system. Lastly, conventional techniques that exploit only the spatial coherence of the SOIs require array and noise calibration information that can be expensive or impossible to obtain, and must detect and localize (DF) all the emitters in the environment in order to copy and recognize the signals of primary interest to the array.

This paper presents a general method for using the known *structure* of communication signals to blindly extract (copy) those signals from co-channel interference environments, and for providing improved DF of those signals. The methodology is based on *maximum-likelihood (ML)* parameter estimation procedures, and is applicable to broad classes of environments, processor structures, and signal modulation formats.

The estimator is also extended to blind *multitarget* copy and copy-aided DF algorithms in applications where *multiple* SOIs with known properties are received by the array. In particular, it is shown that the ML estimation approach can copy and localize structured SOIs in *severely overloaded* environments where the number of received SOIs is *much greater* than the number of elements in the antenna array. As a result, these techniques are particularly attractive in dense environments and/or low-cost collection systems where limited numbers of antennas are available to the processing system.

2. BLIND WAVEFORM ESTIMATOR

2.1. Multiple-SOI Environment Model

A signal model appropriate for environments that contain *multiple* structured SOIs has a complex baseband representation for the received data $\{\mathbf{x}(n)\}_{n=1}^{N}$

$$\mathbf{x}(n) = \mathbf{i}(n) + \mathbf{A_S}\mathbf{s}(n) \quad (1)$$

$$\Leftrightarrow \quad \mathbf{X} = \mathcal{I} + \mathbf{S}\mathbf{A_S}, \quad (2)$$

where $\mathbf{S}$ is a matrix containing L unknown deterministic SOI waveforms such that $\{\mathbf{S}\}_{nl} \equiv s_l^*(n)$ and $\mathbf{A_S}$ is the $M \times L$ matrix of steering vectors for each of those SOIs, and where $\mathcal{I}$ is the Hermitian of a matrix whose columns are circularly-symmetric complex-Gaussian random vectors of zero mean and unknown covariance matrix (ACM) $\mathbf{R_i i}$, containing all of the unstructured noise and interferers in the environment. The ML estimates of $\mathbf{A_S}$, $\mathbf{R_{ii}}$, and $\mathbf{S}$ are then given by the minimizers of the joint *multitarget* maximum-likelihood cost function

$$\mathrm{F_{ML}}\left(\mathbf{S}, \mathbf{A}_s, \mathbf{R_{ii}}\right) = N \ln\left[\left(\mathbf{R_{ii}}\right)\right] - \mathrm{Tr}\left\{\mathbf{R_{ii}}^{-1}\left(\mathbf{X} - \mathbf{S}\mathbf{A_S}^H\right)^H\left(\mathbf{X} - \mathbf{S}\mathbf{A_S}^H\right)\right\} \quad (3)$$

If the interference ACM $\mathbf{R_{ii}}$ is an unknown positive-definite Hermitian matrix, $\mathbf{A_S}$ is an unknown and unconstrained complex matrix, and $\mathbf{S}$ is constrained to be a member of a *multiple-SOI property set* $\mathcal{D}_{\mathbf{S}}$, then the ML estimates of $\mathbf{A_S}$, $\mathbf{R_{ii}}$, and $\mathbf{S}$ are given by [3]

$$\hat{\mathbf{A}}_s\Big|_{\mathrm{ML}} = \mathbf{X}^H\mathbf{S}\left(\mathbf{S}^H\mathbf{S}\right)^{-1}, \quad (4)$$

$$\hat{\mathbf{R}}_{\mathbf{ii}}\Big|_{\mathrm{ML}} = \frac{1}{N}\left[\mathbf{X}^H\mathbf{P}_\perp(\mathbf{S})\,\mathbf{X}\right] \quad (5)$$

$$\hat{\mathbf{S}}_{\mathrm{ML}} = \arg\min_{\mathbf{S}\in\mathcal{D}_{\mathbf{S}}} \mathrm{F}_{\mathrm{ML}}(\mathbf{S}), \quad (6)$$

$$\mathrm{F}_{\mathrm{ML}}(\mathbf{S}) = \frac{\det\left[\mathbf{S}^H\mathbf{P}_\perp(\mathbf{X})\,\mathbf{S}\right]}{\det\left(\mathbf{S}^H\mathbf{S}\right)}, \quad (7)$$

$$\mathrm{F}_{\mathrm{ML}}(\mathbf{S}) = \min_{\mathbf{W}} \mathrm{F}_{\mathrm{ML}}(\mathbf{S},\mathbf{W})$$

$$\mathrm{F}_{\mathrm{ML}}(\mathbf{S},\mathbf{W}) \equiv \frac{\|\mathbf{S}-\mathbf{X}\mathbf{W}\|^2}{\det(\mathbf{S}^H\mathbf{S})} \quad (8)$$

where F_{ML} is the concentrated *multitarget* ML cost function, the Frobenius matrix norm is used in the numerator of (8) and $P_\perp(\mathbf{B})$ is the orthogonal projection operator defined by $P_\perp(\mathbf{B}) \equiv \mathbf{I} - P(\mathbf{B})$ and $P(\mathbf{B}) \equiv \mathbf{B}(\mathbf{B}^H\mathbf{B})^{-1}\mathbf{B}^H$. The formulation of the objective function in (8) is useful for analyzing the property set constraint in the optimization of (6).

Note that F_{ML} differs markedly from the cost function used in conventional multitarget ML sequence estimation [8], due to the assumption of unknown interference ACM $\mathbf{R_{ii}}$ in the formulation of (7). This assumption is warranted if $\mathbf{i}(n)$ contains unknown spatially coherent or incoherent interference, for example, unstructured interfering waveforms, low-level (uncollectable) structured waveforms, or environment-limited background noise. In some cases, this interference may be much stronger than the structured signals of interest, for example, if the collection system is operating in a jammed environment.

The general multitarget cost function can be difficult to optimize in practice, due to the complexity introduced by the determinant operation in (7). However, the cost function can be manipulated to yield powerful multitarget estimation strategies in many practical collection environments by using alternating directions optimization. This strategy holds all signals except one fixed, and optimizes over the single unknown signal. The process is repeated for the other signals. The analysis for each optimization step is comparable to the single SOI problem. The resultant algorithm typically yields time-varying and/or nonlinear processing structures (depending on the SOI properties being exploited by the processor), and can provide copy performance well beyond that obtained by conventional linear time-invariant antenna arrays.

In particular, the multitarget ML estimator can blindly extract structured SOIs from *conventionally overloaded* environments containing $L > M$ SOI waveforms, with mean-square error (MSE) well beyond the minimum MSE obtainable by linear processors in the same environment. This performance is demonstrated in the briefing package [1] for a 4-element antenna array receiving 8 noise-modulated FM signals, and by a *single*-element collection system receiving 10 data-modulated CPFSK signals.

2.2. Single SOI Solutions for Various Property Sets

The analysis for the case of a single SOI is illustrative of the copy-aided technique and provides a basis for obtaining the multi-target SOI estimation.

If $\mathbf{s} \equiv \mathbf{S}$ consists of a single constant modulus SOI, then (8) can be optimized by the *constant modulus property-mapping recursion*,

$$\hat{\mathbf{w}} \leftarrow \left(\mathbf{X}^H\mathbf{X}\right)^{-1}\mathbf{X}^H\hat{\mathbf{s}} \quad (9)$$

$$\hat{\mathbf{s}} \leftarrow \mathrm{CL}\{\mathbf{X}\hat{\mathbf{w}}\} \quad (10)$$

Recursion (9)-(10) is then continued until $\hat{\mathbf{s}}$ and $\hat{\mathbf{w}}$ converge to fixed values. Recursion (9)-(10) is identical to the *least-squares CMA (LSCMA)* first introduced in [2]. As shown in [3], the recursion can also be extended to signals with known or periodically repeating modulus distribution.

If $s(n)$ lies within a known linear subspace (6) can be solved in closed form. For example, if $\mathcal{D}_{\mathbf{S}}$ is the set of time or frequency limited waveforms, the signal property set is given by

$$\mathcal{D}_{\mathbf{S}} = \left\{\mathbf{z}\in\mathcal{C}^N \,:\, \mathbf{z} = \mathbf{P_S}\mathbf{z}\right\} \quad (11)$$

for some known linear projection operator $\mathbf{P_S}$, and generates ML waveform estimate

$$\hat{\mathbf{s}}_{\mathrm{ML}} = \mathbf{X_S}\hat{\mathbf{w}}_{\mathrm{ML}} \quad (12)$$

$$\hat{\mathbf{w}}_{\mathrm{ML}} = \arg\max_{\mathbf{w}} \frac{\mathbf{w}^H\left(\mathbf{X}_{\mathbf{S}}^H\mathbf{X_S}\right)\mathbf{w}}{\mathbf{w}^H\left(\mathbf{X}_\perp^H\mathbf{X}_\perp\right)\mathbf{w}}, \quad (13)$$

where $\mathbf{X_S} = \mathbf{P_S}\mathbf{X}$ and $\mathbf{X}_\perp = \mathbf{X} - \mathbf{X_S}$ are the projections of the received data $\mathbf{X}$ onto the subspace containing the SOI and orthogonal to the SOI, respectively.

If $s(n)$ possesses perfect conjugate self-coherence after removal of a known modulation (e.g., a complex sinusoid), then the signal property set is given by

$$\mathcal{D}_{\mathbf{S}} = \left\{\mathbf{z}\in\mathcal{C}^N \,:\, \mathbf{z} = bz^*\right\} \quad (14)$$

after removal of the known modulation factor. This generates the ML waveform estimate [7]

$$\hat{\mathbf{s}}_{\mathrm{ML}} = \mathrm{Re}\{\mathbf{X}\hat{\mathbf{w}}_{\mathrm{ML}}\} \quad (15)$$

$$\hat{\mathbf{w}}_{\mathrm{ML}} = \arg\max_{\mathbf{w}} \frac{\mathrm{Re}\left\{\mathbf{w}^T\left(\mathbf{X}^T\mathbf{X}\right)\mathbf{w}\right\}}{\mathbf{w}^H\left(\mathbf{X}^H\mathbf{X}\right)\mathbf{w}}. \quad (16)$$

3. EXTENSION TO COPY-AIDED DOA ESTIMATORS

The methodology used to develop the ML constant modulus waveform estimator can be used to develop DOA estimators that also exploit the additional structure of the SOI waveforms. In particular, the ML estimation procedure

can be used to derive a generic class of DOA estimators referred to here as *copy-aided DF algorithms*, by using the waveform estimate provided by a blind copy "front-end" to estimate the DOA of the waveform captured by that front-end.

This is accomplished by considering the DOA estimate of a *known* SOI $\mathbf{s}$ received from an unknown DOA with an unknown complex gain (power level and phase shift). Assuming reception by a narrowband antenna array, the received data signal $\mathbf{X}$ has complex baseband representation

$$\mathbf{X} = \mathcal{I} + \mathbf{s}\mathbf{a}_s^H \quad (17)$$

$$\mathbf{a}_s = g_s\mathbf{a}(\theta_s) \quad (18)$$

where g_s and θ_s are the unknown gain and DOA of $\mathbf{s}$, and where $\mathcal{I}$ is given by (2) and $\{\mathbf{a}(\theta)\}$ is the DOA manifold of the array. Optimizing the ML objective function obtained from the model in (17) with respect to $\mathbf{R_{ii}}$, g_s, and θ_s and removing constant terms yields

$$\hat{\mathbf{R}}_{\mathbf{ii}}\Big|_{\mathrm{ML}} = \hat{\mathbf{R}}_{\mathbf{ii}} + \hat{\varepsilon}\left(\hat{g}_s, \hat{\theta}_s\right)\hat{\varepsilon}^H\left(\hat{g}_s, \hat{\theta}_s\right)\hat{R}_{ss} \quad (19)$$

$$\hat{\varepsilon}\left(g, \theta\right) \triangleq g\mathbf{a}\left(\theta\right) - \hat{\mathbf{a}}_s$$

$$\hat{g}_s\big|_{\mathrm{ML}} = \frac{\mathbf{a}^H(\theta)\hat{\mathbf{R}}_{\mathbf{XX}}^{-1}\hat{\mathbf{a}}_s}{\hat{\mathbf{a}}_s^H\hat{\mathbf{R}}_{\mathbf{XX}}^{-1}\hat{\mathbf{a}}_s} \quad (20)$$

$$\hat{\theta}_s\big|_{\mathrm{ML}} = \arg\max_{\theta} \mathrm{S}_{\mathrm{ML}}(\theta) \quad (21)$$

$$\mathrm{S}_{\mathrm{ML}}(\theta) \triangleq \frac{\left|\hat{\mathbf{a}}_s^H\hat{\mathbf{R}}_{\mathbf{XX}}^{-1}\mathbf{a}(\theta)\right|^2}{\left[\hat{\mathbf{a}}_s^H\hat{\mathbf{R}}_{\mathbf{XX}}^{-1}\hat{\mathbf{a}}_s\right]\left[\mathbf{a}^H(\theta)\hat{\mathbf{R}}_{\mathbf{XX}}^{-1}\mathbf{a}(\theta)\right]} \quad (22)$$

where $\hat{\mathbf{a}}_s$ and $\hat{\mathbf{R}}_{\mathbf{ii}}$ are the *unconstrained* ML estimates of $\mathbf{a}_s$ and $\mathbf{R_{ii}}$ given in (4)-(5) and where $\hat{\mathbf{R}}_{\mathbf{XX}}$ and $\hat{R}_{ss}$ are the ACM of $\mathbf{x}(n)$ and $s(n)$ measured over the collect interval. $\mathrm{S}_{\mathrm{ML}}(\theta)$ can be interpreted as a *DOA spectrum* ranging between 0 and 1 is maximized when the "angle" between $\hat{\mathbf{a}}_s$ and $\mathbf{a}(\theta)$ is minimized. $\mathrm{S}_{\mathrm{ML}}(\theta)$ can also be expressed using the least-squares copy vector $\hat{\mathbf{w}}_{\mathrm{LS}} = \left(\mathbf{X}^H\mathbf{X}\right)^{-1}\mathbf{X}^H\mathbf{s}$ that minimizes the mean-square error between $\mathbf{s}$ and $\mathbf{Xw}$,

$$\mathrm{S}_{\mathrm{ML}}(\theta) = \frac{\left|\hat{\mathbf{w}}_{\mathrm{LS}}^H\mathbf{a}(\theta)\right|^2}{\left[\hat{\mathbf{w}}_{\mathrm{LS}}^H\hat{\mathbf{R}}_{\mathbf{XX}}\hat{\mathbf{w}}_{\mathrm{LS}}\right]\left[\mathbf{a}^H(\theta)\hat{\mathbf{R}}_{\mathbf{XX}}^{-1}\mathbf{a}(\theta)\right]}. \quad (23)$$

Equation (23) motivates the *ML-like* copy-aided DF algorithm [9], given by

$$\hat{\theta}_s = \arg\max_{\theta} \mathrm{S}(\theta; \hat{\mathbf{w}}_s) \quad (24)$$

$$\mathrm{S}\left(\theta; \mathbf{w}\right) \triangleq \frac{\left|\hat{\mathbf{w}}^H\mathbf{a}\left(\theta\right)\right|^2}{\left[\hat{\mathbf{w}}^H\hat{\mathbf{R}}_{\mathbf{XX}}\hat{\mathbf{w}}\right]\left[\mathbf{a}^H\left(\theta\right)\hat{\mathbf{R}}_{\mathbf{XX}}^{-1}\mathbf{a}\left(\theta\right)\right]} \quad (25)$$

where $\hat{\mathbf{w}}_s$ is a set of blind signal copy weights used to extract an *arbitrary* structured SOI $s(n)$ from a received data set $\mathbf{x}(n)$. Equation (25) is referred to as the *ML-like DOA spectrum*, due to its similarity with the maximum-likelihood objective function given in (23). The spectrum ranges between 0 and 1 and has a global maximum in the vicinity of the SOI DOA θ_s if $\mathbf{w}_s^H\mathbf{x}(n)$ provides an accurate estimate of $s(n)$. The algorithm can also be used in environments containing multiple SOIs, if each of those SOIs can be accurately estimated by its own signal copy vector.

The ML-like spectra are *signal-specific*, in the sense that they are uniquely defined for each signal copy vector, and have a global maximum in the direction of the signal captured by that copy vector. The ML-like spectra also do not require knowledge of the background noise covariance matrix or the number of received emitter wavefronts L to operate, and can be used with any signal copy "front-end" that can provide usable copy weights. As a consequence, the technique has important implementation advantages over conventional DOA estimators that require optimization of multimodal or multidimensional objective functions to simultaneously determine all of the wavefront DOAs, and that are heavily dependent on prior knowedge (or correct estimation) of the noise covariance or the number of received wavefronts. In addition, it can be shown that the ML-like spectrum adheres to a DF error bound (referred to here as the *single-SOI Cramer-Rao DF error bound*) that can be significantly lower than error bounds adhered to by conventional techniques, and that the estimator can resolve $\geq M$ co-channel wavefronts using an M-sensor antenna array.

A true *joint* maximum-likelihood estimate of the SOI waveform and DOA can be obtained if $s(n)$ belongs to a known subspace or has perfect conjugate self-coherence. In the former case, the joint ML DOA and waveform estimate is given by

$$\hat{\theta}_{\mathrm{ML}} = \arg\max_{\theta} \frac{\mathbf{a}^H(\theta)\left(\mathbf{X}_\perp^H\mathbf{X}_\perp\right)^{-1}\mathbf{a}(\theta)}{\mathbf{a}^H(\theta)\left(\mathbf{X}^H\mathbf{X}\right)^{-1}\mathbf{a}(\theta)} \quad (26)$$

$$\hat{\mathbf{s}}_{\mathrm{ML}} = \mathbf{X_S}\mathbf{w}\left(\hat{\theta}_{\mathrm{ML}}\right) \quad (27)$$

$$\mathbf{w}(\theta) = \left(\mathbf{X}_\perp^H\mathbf{X}_\perp\right)^{-1}\mathbf{a}(\theta) \quad (28)$$

This estimator is identical to the ML DOA estimator given in [10] for bandlimited SOIs. In the latter case, the joint DOA and waveform estimate is given by

$$\hat{\theta}_{\mathrm{ML}} = \arg\max_{\theta} \left|\frac{\mathbf{w}^T(\theta)\left(\mathbf{X}^T\mathbf{X}\right)\mathbf{w}(\theta)}{\mathbf{w}^H(\theta)\left(\mathbf{X}^H\mathbf{X}\right)\mathbf{w}(\theta)}\right| \quad (29)$$

$$\hat{\mathbf{s}}_{\mathrm{ML}} = \mathrm{Re}\left\{\mathbf{X}\mathbf{w}(\theta)e^{-j\varphi(\theta)}\right\} \quad (30)$$

$$\mathbf{w}(\theta) = \left(\mathbf{X}^H\mathbf{X}\right)^{-1}\mathbf{a}(\theta) \quad (31)$$

$$\varphi(\theta) = \frac{1}{2}\angle\left[\mathbf{w}^T(\theta)\left(\mathbf{X}^T\mathbf{X}\right)\mathbf{w}(\theta)\right] \quad (32)$$

It can be shown that these estimators reduce to the unconstrained blind copy front-end given by (12)-(13) and (15)-(16), respectively, followed by the ML-like copy-aided DF backend given in (24)-(25), if the time-bandwidth product of $\mathbf{X}$ or $\mathbf{X_S}$ is large.

3.1. Extension to Multiple-SOI Environments

The copy-aided DF procedure described above can also be used to derive *multitarget* copy-aided DOA estimators with much higher accuracy than conventional or (single-SOI) copy-aided DF algorithms. These estimators are derived by assuming reception of multiple known (or estimated) SOIs from differing directions of arrival, such that

the received data signal $\mathbf{X}$ has complex baseband representation

$$\mathbf{X} = \mathcal{I} + \mathbf{S}\mathbf{A_S} \quad (33)$$

$$\mathbf{A_S} = \left[g_1\mathbf{a}\left(\theta_1\right) \cdots g_L\mathbf{a}\left(\theta_L\right)\right] \quad (34)$$

where $\{g_\ell\}_{\ell=1}^L \leftrightarrow \mathbf{g}_s$ and $\{\theta_\ell\}_{\ell=1}^L \leftrightarrow \theta_s$ are the unknown gains and DOAs of $\{\mathbf{s}_\ell\}_{\ell=1}^L \leftrightarrow \mathbf{S}$, and where $\mathcal{I}$ is given by (2) and $\{\mathbf{a}(\theta)\}$ is the DOA manifold of the array. Estimation of the SOI DOAs θ_s is then accomplished by minimizing (3) with respect to $\mathbf{R_{ii}}$, $\mathbf{g}_s$, and θ_s, using the constrained steering vector model given in (34).

Formulation of the multitarget copy-aided DF estimator is beyond the scope of this paper. However, a computationally simple approach has been developed in [11], which provides a separate signal specific copy-aided DOA estimator for every SOI captured by a multitarget copy front-end. Each estimator has a global maximum in the direction of the SOI captured by the copy front-end, and is optimized via a single dimensional search over DOA. In addition, each estimator is immune to DF/modelling errors induced in the other DOA estimators, does not require knowledge of the background interference covariance matrix to operate, and adheres to a DF error bound that can be much lower than the conventional unaided or (single-SOI) copy-aided Cramer-Rao DF error bounds. Lastly, the algorithm can operate under *much* more severe loading conditions than either of the conventional estimators, especially if the SOI estimates are provided using the multitarget approach described in Section 2.1. As a result, the algorithm retains all of the implementation advantages of the single-SOI copy-aided DF algorithm, with additional gains in DF accuracy and robustness in dense interference environments.

4. SIMULATION RESULTS

Extensive simulation results are provided for these estimators in [1]. These simulations demonstrate the following performance results:

- blind acquisition and copy of two simulated burst-CPFSK waveforms in the presence of two severe structured and unstructured co-channel interference using a four-element linear antenna array, with copy performance nearly equal to accuracies attained by the nonblind linear array;;
- blind acquisition and copy of three real FM waveforms using a 3-element linear antenna array, with copy performance nearly equal to accuracies attained by the nonblind linear array;
- blind separation of *eight* (8) co-channel noise-modulated FM waveforms using a 4-element antenna array and a multitarget ML estimator, with copy performance *well beyond* accuracies attained by the nonblind linear array;
- blind separation and demodulation of *ten* (10) co-channel data-modulated CPFSK waveforms using a single- sensor collector, based on the CPFSK structure of the SOIs, with demodulation performance well beyond accuracies attained by the nonblind demodulator;
- copy-aided DF of burst, BPSK, and FM SOIs copied by single-target and multitarget processor front-ends, with DF performance well beyond accuracies attained by conventional unaided DF approaches.
- copy-aided DF of *all eight* of the FM SOIs captured by the multitarget ML waveform estimator, at DF performance well beyond accuracies attained by conventional unaided or (single-SOI) copy-aided DF algorithms.

These results underscore the utility of the maximum-likelihood estimation approach, especially in overloaded environments where the number of co-channel emitters overwhelms the capabilities of conventional linear processing techniques.

5. CONCLUSIONS

A general approach for blind adaptive signal processing, based on maximum-likelihood estimation of signals and parameters with known properties received by antenna arrays, is presented. ML waveform and wavefront DOA estimators are developed for operation in environments containing multiple constant modulus signals, for example, FM and CPFSK communication signals, and demonstrated for environments containing multiple co-channel FM and CPFSK waveforms. The ML waveform and DOA estimation concept is also extended to burst, agile, and transient waveforms with limited time and/or frequency support, and to BPSK and DSB-AM waveforms with constant phase characteristics. These results are demonstrated in the briefing package [1].

The ML estimation approach developed here can also be generalized in a number of different manners. The specific approaches presented here are easily extended to transmitted signals with more complex modulus properties, for example, burst BPSK waveforms. The ML estimator can also be extended to wideband collection systems where the SOIs are received in the presence of frequency-selective interference and channel distortion (multipath).

6. REFERENCES

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