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SELF-COHERENCE RESTORAL: A NEW APPROACH TO BLIND ADAPTATION OF ANTENNA ARRAYS

Brian G. Agee, Stephan V. Schell, William A. Gardner [1]

Department of Electrical Engineering and Computer Science
University of California, Davis, CA 95616

ABSTRACT

A new approach to blind adaptation of antenna arrays is presented that has the capability to extract cyclostationary (e.g., PCM, FDM-FM and AM) signals from co-channel interference environments using only known spectral correlation properties (e.g., known baud-rate, pilot-tone frequency, or carrier frequency) of those signals. The new class of *Self-COherence REstoral (SCORE)* objective functions is introduced, and algorithms for adapting sensor arrays to optimize these objective functions are developed. It is shown analytically and by computer simulation that these algorithms will maximize the SINR at the output of a sensor array when a single desired signal with spectral correlation at a known value of frequency separation (e.g., baud-rate) and an arbitrary number of interferers without correlation at that frequency separation are impinging on the array.

1. INTRODUCTION

The fundamental problem facing any adaptive receiver designer is how to distinguish signals of interest (SOIs) from the surrounding noise and interference in order to train the receiver processor. This is a particularly important problem in mobile and satellite communication systems, where unknown SOIs and interference may be impinging on the receiver from unknown or rapidly-changing directions. In these environments, it may be impossible or too costly for the receiver to employ conventional adaptive techniques that exploit knowledge of the signal direction of arrival [1], digital modulation format [2], or waveform (e.g., if a known preamble or pilot signal [2] is transmitted with the SOI). Techniques that perform *blind* signal extraction, i.e., that exploit simpler and/or more general properties of the SOI or interference waveforms, must be developed before adaptive receivers can be used in these applications.

The new *Self-COherence REstoral (SCORE)* approach has the potential to provide this capability. A property shared by most communication signals is that they are *self-coherent* or *conjugate self-coherent* at discrete nonzero values of frequency separation ([3], [4]). Self-coherence is commonly induced by periodic switching, gating, mixing or multiplexing operations at the transmitter. For instance, self-coherence is induced at multiples of the baud-rate in PCM signals and at multiples of the pilot-tone frequency in FDM-FM signals. Conjugate self-coherence is commonly induced by unbalanced in-phase and quadrature carrier modulation at the transmitter. For instance, conjugate self-coherence is induced at twice the carrier frequency in DSB-AM, VSB-AM and BPSK signals.

The self-coherence (or conjugate self-coherence) of a received signal degraded if it is corrupted by additive interference which does not share that coherence, e.g., if a PCM SOI is corrupted at the receiver by a PCM interference signal modulated at a different baud-rate. This paper presents a development, analysis and experimental verification of the new class of *SCORE algorithms*, which adapt a receiver processor to *restore* the SOI self-coherence (or conjugate self-coherence) to the receiver output signal.

2. SELF-COHERENCE CONCEPT

A waveform $x(t)$ is said to be *self-coherent at frequency* α if the cross-correlation between $x(t)$ and $x(t)$ frequency-shifted by α is nonzero at some lag τ, i.e., if

$$R_{xx}^{\alpha}(\tau) \triangleq < x(t+\tau/2)\,[x(t-\tau/2)e^{j2\pi\alpha t}]^* >_\infty$$
$$= < x(t+\tau/2)\,x^*(t-\tau/2)e^{-j2\pi\alpha t} >_\infty \neq 0 \qquad (2\text{-}1)$$

at some lag τ, where $< \cdot >_\infty$ denotes infinite time-averaging. A waveform $x(t)$ is said to be *conjugate self-coherent at frequency* α if the cross-correlation between $x(t)$ and the *conjugate* of $x(t)$ frequency-shifted by α is nonzero at some lag τ, i.e., if

$$R_{xx^*}^{\alpha}(\tau) \triangleq < x(t+\tau/2)\,[x^*(t-\tau/2)e^{j2\pi\alpha t}]^* >_\infty$$
$$= < x(t+\tau/2)\,x(t-\tau/2)e^{-j2\pi\alpha t} >_\infty \neq 0 \qquad (2\text{-}2)$$

at some lag τ. The functions $R_{xx}^{\alpha}(\tau)$ and $R_{xx^*}^{\alpha}(\tau)$ are referred to here as the *cyclic autocorrelation function (cyclic ACF)* and the *cyclic conjugate-correlation function (cyclic CCF)*, respectively. The cyclic ACF and CCF generalize to the *cyclic autocorrelation matrix* and *cyclic conjugate correlation matrix*

$$\mathbf{R}_{\mathbf{xx}}^{\alpha}(\tau) \triangleq < \mathbf{x}(t+\tau/2)\,\mathbf{x}^{\dagger}(t-\tau/2)\,e^{-j2\pi\alpha t} >_\infty \qquad (2\text{-}3)$$

$$\mathbf{R}_{\mathbf{xx}^*}^{\alpha}(\tau) \triangleq < \mathbf{x}(t+\tau/2)\,\mathbf{x}^{T}(t-\tau/2)\,e^{-j2\pi\alpha t} >_\infty \qquad (2\text{-}4)$$

when $\mathbf{x}(t)$ is a multidimensional waveform, e.g., the output of an antenna array. These functions are developed detail in the new *theory of spectral correlation* for modelling of *cyclostationary* and *almost-cyclostationary*

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waveforms ([3], [4]). In [3] and [4], it is shown that complex cyclostationary and almost-cyclostationary waveforms exhibit self-coherence and/or conjugate self-coherence at one or more discrete nonzero values of frequency separation, viz., at multiples of the time-periodicity (or periodicities) of the waveform statistics.

A useful measure of the strength of the self-coherence that a given signal exhibits at some value of frequency separation α is the correlation coefficient between $x(t)$ and $x(t-\tau)e^{j2\pi\alpha t}$

$$\rho^{\alpha}_{xx}(\tau) \triangleq \frac{\langle x(t+\tau/2)x^*(t-\tau/2)\,e^{-j2\pi\alpha t}\rangle_\infty}{\sqrt{\langle |x(t+\tau/2)|^2\rangle_\infty \langle |x(t-\tau/2)e^{j2\pi\alpha t}|^2\rangle_\infty}}$$

$$= R^{\alpha}_{xx}(\tau)/R_{xx}(0) \qquad (2\text{-}5)$$

This function is referred to here as the *self-coherence function (SCF)* of $x(t)$ at frequency-separation α and lag τ. An analogous *conjugate self-coherence function (CSCF)* can also be defined to measure conjugate self-coherence,

$$\rho^{\alpha}_{xx^*}(\tau) \triangleq R^{\alpha}_{xx^*}(\tau)/R_{xx}(0) \qquad (2\text{-}6)$$

The SCF (and CSCF) can be used together with the Orthogonal Projection Theorem to derive the useful relationship

$$x^{(*)}(t-\tau)e^{j2\pi\alpha t} = \rho^{\alpha}_{xx^{(*)}}(\tau)^* e^{j\pi\alpha\tau}x(t) + \sqrt{1-|\rho^{\alpha}_{xx^{(*)}}(\tau)|^2}\,\epsilon_{xx^{(*)}}(t) \qquad (2\text{-}7)$$

where the conjugation in parentheses "$(*)$" is applied if and only if conjugate self-coherence is being measured, and where $x(t)$ and $\epsilon_{xx^{(*)}}(t)$ are equal-power uncorrelated waveforms.

The utility of the self-coherence concept can best be seen in interference environments. Consider the environment where a scalar waveform $x(t)$ is equal to a scaled SOI plus independent additive interference (noise and co-channel interference), $x(t) = a\,s(t) + i(t)$. Assume that SOI $s(t)$ is self-coherent at frequency α, but that interference $i(t)$ is not self-coherent at that frequency separation. Then the cyclic ACF of $x(t)$ at frequency separation α is given by

$$R^{\alpha}_{xx}(\tau) = |a|^2 R^{\alpha}_{ss}(\tau) + R^{\alpha}_{ii}(\tau) = |a|^2 R^{\alpha}_{ss}(\tau) \qquad (2\text{-}8)$$

i.e., the cyclic ACF is unchanged (after infinite time-averaging) by the addition of *arbitrary* interference, provided that interference is *not* self-coherent at frequency-separation α.

A useful interpretation of (2-8) is that the frequency-shift (and conjugation) operation inherent to the cyclic ACF (or cyclic CACF) computation *completely decorrelates* the interference, but only *partially decorrelates* the SOI, if the SOI and interference are not self-coherent (or conjugate self-coherent) at the same frequency separations. This interpretation can be mathematically expressed by using (2-7) to show that

$$x^{(*)}(t-\tau)e^{j2\pi\alpha t} = \hat{a}\,s(t) + \hat{i}(t) \qquad (2\text{-}9)$$

where

$$\hat{i}(t) = a\sqrt{1-|\rho^{\alpha}_{ss^{(*)}}(\tau)|^2}\,\epsilon_{ss^{(*)}}(t) + i(t-\tau)e^{j2\pi\alpha t} \qquad (2\text{-}10)$$

$$\hat{a} = a\,\rho^{\alpha}_{ss^{(*)}}(\tau)^*\,e^{j\pi\alpha\tau} \qquad (2\text{-}11)$$

i.e., where $\hat{i}(t)$ is uncorrelated with both $s(t)$ and $i(t)$ (and therefore $x(t)$).

3. LEAST-SQUARES SCORE ALGORITHM

The first class of SCORE algorithms can be developed using equation (2-9). Consider the environment where a multisensor antenna array is excited by a single SOI with self-coherence at a known value of frequency separation α and by noise and co-channel interference without self-coherence at α. Further assume that no far-field multipath is present in this environment, i.e., that no significantly-delayed replicas of $s(t)$ are also received by the array, and that the SOI and interference are narrowband with respect to the RF frequency of the array receivers. Then the complex baseband or analytic representation of the multisensor received signal $\mathbf{x}(t)$ can be modelled by

$$\mathbf{x}(t) = \mathbf{A}\,s(t) + \mathbf{I}(t) \qquad (3\text{-}1)$$

Vector $\mathbf{A}$, referred to here as the *SOI aperture vector*, models the polarization and direction-of-arrival (DOA) dependent sensor antenna gains, cross-sensor phase-mismatches, and near-field multipath effects, e.g., due to scattering off of receiver structures and mutual coupling between array elements. Interference field $\mathbf{I}(t)$ models the remaining signals and background noise received by the array.

The goal here is to linearly combine the elements of $\mathbf{x}(t)$ to enhance the SOI and suppress the noise and interference received by the array, *without* using knowledge of the SOI waveform, SOI aperture vector, or interference autocorrelation matrix to train the linear combiner weights. As a performance benchmark, the *maximum-SINR* linear-combiner output signal is given by

$$y(t) = \mathbf{w}^{\dagger}_{max}\mathbf{x}(t), \quad \mathbf{w}_{max} \propto \mathbf{R}_{II}(0)^{-1}\mathbf{A} \propto \mathbf{R}_{xx}(0)^{-1}\mathbf{A}\,R_{ss}(0) \qquad (3\text{-}2)$$

These weights can also be interpreted as the optimal solution to least-squares cost function

$$F_{LS}(\mathbf{w}) \triangleq \langle |y(t) - \hat{a}\,s(t)|^2\rangle_\infty, \quad y(t) = \mathbf{w}^{\dagger}\mathbf{x}(t) \qquad (3\text{-}3)$$

where $\hat{a}$ is an arbitrary (nonzero) scalar constant (which is assumed to have no effect on the output signal quality). The goal is therefore to find a method for adapting $\mathbf{w}$ to approximate the maximum-SINR processor, using *only* knowledge of the self-coherence or conjugate self-coherence of the SOI.

Define *control signal* $u(t) \triangleq \mathbf{c}^{\dagger}\mathbf{x}(t)$, where $\mathbf{c}$ is an arbitrary *control vector*. Use of (3-1) and (2-9) yields

$$u(t) = \mathbf{c}^{\dagger}[\mathbf{A}\,s(t) + \mathbf{I}(t)] = a\,s(t) + i(t) \qquad (3\text{-}4)$$

$$\Rightarrow u^{(*)}(t-\tau)e^{j2\pi\alpha t} = \hat{a}\,s(t) + \hat{i}(t) \qquad (3\text{-}5)$$

where $\hat{i}(t)$ and $\hat{a}$ are given by (2-10) and (2-11), and where $\hat{i}(t)$ is uncorrelated with $s(t)$ and $i(t)$ (and therefore $x(t)$) if $\mathbf{I}(t)$ is not self-coherent (or conjugate self-coherent) at α. Define the *least-squares SCORE cost function*

$$F_{SCORE}(\mathbf{w}) \triangleq < |y(t) - r(t)|^2 >_T \quad (3\text{-}6)$$

where *reference signal r(t)* is defined by

$$r(t) \triangleq u^{(*)}(t-\tau)\, e^{j2\pi\alpha t} \quad (3\text{-}7)$$

and where the conjugation is applied iff SOI conjugate self-coherence is being restored by the processor. Substitution of (3-5) and (3-8) into (3-6) yields

$$\begin{aligned} F_{SCORE}(\mathbf{w}) &= < |y(t) - [\hat{a}\, s(t) + \hat{i}(t)]|^2 >_T \\ &\rightarrow < |y(t) - \hat{a}\, s(t)|^2 >_\infty + < |\hat{i}(t)|^2 >_\infty \quad (3\text{-}8) \end{aligned}$$

as the averaging time T goes to infinity. Since $\hat{i}(t)$ is not a function of $\mathbf{w}$, (3-6) is therefore asymptotically equivalent to the true least-squares cost function (3-3).

This result can also be obtained by solving for the optimum processor weight vector $\mathbf{w}$ in (3-6), yielding

$$\begin{aligned} \mathbf{w}_{SCORE} &= < \mathbf{x}(t)\mathbf{x}^\dagger(t) >_T^{-1} < \mathbf{x}(t) r^*(t) >_T \quad (3\text{-}10) \\ &\rightarrow e^{j\pi\alpha\tau}\, \mathbf{R}_{\mathbf{xx}}(0)^{-1}\, \mathbf{R}^{\alpha}_{\mathbf{xx}(*)}(\tau)\, \mathbf{c}^{(*)} \quad (3\text{-}11) \\ &\rightarrow [(\mathbf{A}^\dagger \mathbf{c})^{(*)} \rho^{\alpha}_{ss(*)}(\tau)\, e^{j\pi\alpha\tau}]\, [\mathbf{R}_{\mathbf{xx}}(0)^{-1} \mathbf{A}\, R_{ss}(0)] \\ &\rightarrow \mathbf{w}_{\max} \quad (3\text{-}12) \end{aligned}$$

if $\mathbf{I}(t)$ is not self-coherent (or conjugate self-coherent) at α. Note that $\mathbf{w}_{SCORE}$ converges to the maximum-SINR solution for *arbitrary* control vector $\mathbf{c}$, as long as $\mathbf{c}$ is not orthogonal to $\mathbf{A}$. Equation (3-10) is referred to here as the *least-squares SCORE algorithm.*

The least-squares SCORE processor is shown in Figure 1. It is implemented using an RLS algorithm to adapt the processor weights, with the reference signal given in (3-7) used as the desired signal input. The only control variables required for the reference generation are the control vector $\mathbf{c}$, lag value τ, frequency-shift value α and conjugation control; however, only α and the conjugation control are critical to the operation of the processor. In practice, the use of exponentially-decaying windows in the RLS algorithm allows some tolerance in α [6].

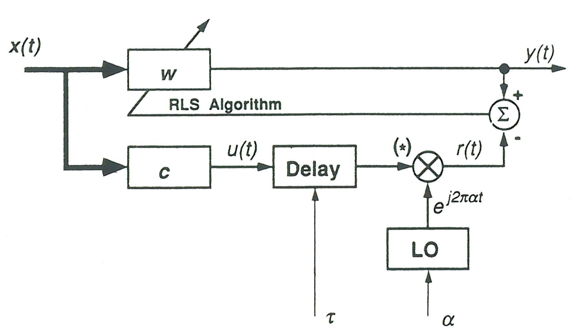

Figure 1: Least-Squares SCORE Processor

4. CROSS-SCORE ALGORITHM

An obvious way to improve the performance of the least-squares SCORE algorithm is to adapt the control vector as well as the processor vector. To accomplish this, we consider the alternative of *maximizing* the *cross-SCORE objective function,* defined here as the magnitude-square of the correlation-coefficient between the processor and reference signals,

$$\hat{F}_{SCORE}(\mathbf{w};\mathbf{c}) \triangleq |\rho_{yr}(0)|^2 = \frac{|\mathbf{w}^\dagger \mathbf{R}^{\alpha}_{\mathbf{xx}(*)}(\tau)\, \mathbf{c}^{(*)}|^2}{[\mathbf{w}^\dagger \mathbf{R}_{\mathbf{xx}}(0)\, \mathbf{w}]\, [\mathbf{c}^\dagger \mathbf{R}_{\mathbf{xx}}(0)\, \mathbf{c}]} \quad (4\text{-}1)$$

where again the conjugation is applied iff conjugate self-coherence is being restored. The cross-SCORE objective function measures the *cross*-coherence (or conjugate cross-coherence) between the processor output signal and the control signal, and is maximized when $\mathbf{w}$ and $\mathbf{c}$ are adjusted to remove the interference from the processor output signal. $\hat{F}_{SCORE}$ also has the same optimal solution (for fixed control vector) as the least-squares SCORE cost function, i.e., $\hat{F}_{SCORE}$ is maximized for fixed $\mathbf{c}$ by setting $\mathbf{w}$ equal to (3-10).

Full optimization of the cross-SCORE objective function can be accomplished by maximizing $\hat{F}_{SCORE}$ first with respect to $\mathbf{w}$ and then with respect to $\mathbf{c}$. Substituting (3-11) into (4-1) yields

$$\hat{F}_{SCORE}(\mathbf{w}_{SCORE};\mathbf{c}) = \frac{\mathbf{c}^\dagger [\mathbf{R}^{\alpha}_{\mathbf{xx}(*)}(\tau)^\dagger \mathbf{R}_{\mathbf{xx}}(0)^{-1} \mathbf{R}^{\alpha}_{\mathbf{xx}(*)}(\tau)]^{(*)}\, \mathbf{c}}{\mathbf{c}^\dagger \mathbf{R}_{\mathbf{xx}}(0)\, \mathbf{c}} \quad (4\text{-}2)$$

Equation (4-2) is maximized with respect to $\mathbf{c}$ by solving the generalized eigenvector equation

$$[\mathbf{R}^{\alpha}_{\mathbf{xx}(*)}(\tau)^\dagger \mathbf{R}_{\mathbf{xx}}(0)^{-1} \mathbf{R}^{\alpha}_{\mathbf{xx}(*)}(\tau)]\, \mathbf{c}_{SCORE} = \lambda\, \mathbf{R}_{\mathbf{xx}}(0)\, \mathbf{c}_{SCORE} \quad (4\text{-}3)$$

for the maximum-eigenvalue eigenvector. The maximum of $\hat{F}_{SCORE}$ is then equal to the maximum eigenvalue of (4-3).

It is easy to show ([5], [6]) that the optimal processor and control vectors will converge to the maximum-SINR solution in the environment modelled in Section 3, and that the optimum cross-SCORE objective function will converge to

$$\hat{F}_{SCORE}(\mathbf{w}_{SCORE};\mathbf{c}_{SCORE}) = \frac{|\rho^{\alpha}_{ss(*)}(\tau)|^2}{[1 + SINR^{-1}_{\max}]^2} \quad (4\text{-}4)$$

where $SINR_{\max}$ is the maximum obtainable SINR,

$$SINR_{\max} = \mathbf{A}^\dagger \mathbf{R}_{\mathbf{II}}(0)^{-1} \mathbf{A}\, R_{ss}(0) \quad (4\text{-}5)$$

5. SCORE ALGORITHM SIMULATIONS

The simulated receiver geometry is as follows. A four-element circular array with a 20.48 MHz bandwidth and a half-wavelength diameter is excited by white Gaussian thermal noise, a BPSK SOI incident at a 60° DOA, an MSK interferer incident at a -110° DOA, and two CW interferers incident at -45° and 30° DOAs. The SOI has a 5.12 Mb/s baud-rate, a 0 MHz carrier offset, and a 20 dB input signal-to-white-noise ratio (SWNR) on each antenna element. The MSK interferer has a 10.24 Mb/s baud-rate, a 0 MHz carrier offset, and a 30 dB input SWNR. The CW interferers have 1 MHz and -2.5 MHz carrier offsets, and 40 dB and 33 dB input SWNRs, respectively.

Two experiments are performed. In the first experiment, the SCORE processor is set to restore self-coherence at the SOI baud-rate: the frequency-shift is set to 5.12 MHz, the delay is set to 98 nsec (one-half baud), and the conjugation is not used in (3-7). In the second simulation, the SCORE processor is set to restore self-coherence at twice the SOI carrier offset: the frequency-shift and delay are set to zero and the conjugation is used in (3-7). Performance measures are obtained for the least-squares SCORE algorithm with the control vector set to $[1\,0\,0\,0]^T$ and the processor vector exactly optimized using (3-10) over averaging interval $[0,\ T]$ at each time T in the simulation run, and for the cross-SCORE algorithm with the processor and control vectors exactly optimized using (3-10) and (4-3) (or equivalent if conjugate self-coherence is being restored).

The performance measure used to judge the quality of the processor output signal is the *output SINR*, defined by

$$\text{SINR} \triangleq |\mathbf{w}^\dagger \mathbf{A}|^2 R_{ss}(0) \,/\, \mathbf{w}^\dagger \mathbf{R}_{II}(0)\,\mathbf{w} \qquad (5\text{-}1)$$

where $\mathbf{A}$, $R_{ss}(0)$ and $\mathbf{R}_{II}(0)$ are the true SOI aperture, SOI power and interference autocorrelation matrix, respectively. As a benchmark, the SINR of the true least-squares processor which uses $r(t) = s(t)$ is also computed and displayed with the SCORE SINRs in both simulations. Simulation results are shown in Figures 2 and 3.

These Figures verify the theoretical results derived in Sections 3 and 4. In both experiments, the least-squares SCORE processor SINR converges to within 3 dB of the maximum attainable SINR within 1000 SOI bauds (200 μsec), using only the knowledge of the SOI baud-rate (Figure 2) or carrier frequency offset (Figure 3). This convergence time is dramatically improved when the cross-SCORE algorithm is used to adapt the processor: the baud-rate restoring SCORE SINR converges to within 3 dB of the maximum attainable SINR within 100 SOI bauds (20 μsec), while the carrier-restoring cross-SCORE algorithm converges in under 10 SOI bauds (2 μsec). These results compare to the true processor SINR, which converges in this environment in about 5 SOI (1 μsec), using knowledge of the entire SOI waveform.

The relatively slow convergence of the least-squares SCORE algorithm is due the large uncorrelated interference component $\hat{i}(t)$ present in the reference signal $r(t)$ used in (3-10). Until $\hat{i}(t)$ is averaged out by the correlation process, it will have a strong effect on the adaptation of the processor weights. This effect is greatly reduced in the cross-SCORE algorithm, which adapts the control vector to cancel the received interference $i(t)$ before it reaches $r(t)$. The primary corruption remaining in $r(t)$ after the control vector is optimized is the nonremovable $\sqrt{1-|\rho_{ss(\cdot)}^{\alpha}(\tau)|^2}\ \epsilon_{ss(\cdot)}(t)$ component of $\hat{i}(t)$ given in (2-11). This explains the very fast convergence of the carrier-restoring cross-SCORE algorithm, since the CSCF of a BPSK SOI has unity magnitude at α equal to twice the SOI carrier offset ([3], [4]).

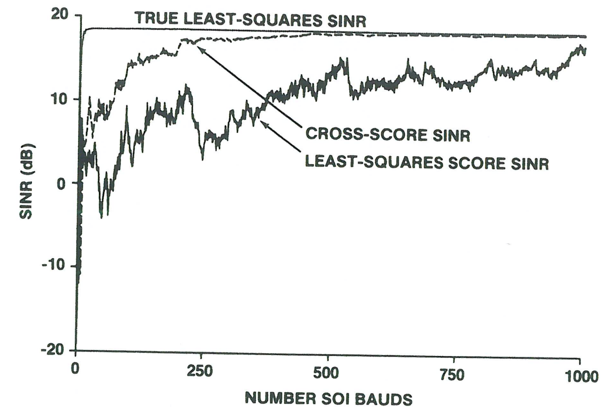

Figure 2: Baud-Rate Restoring SCORE SINRs

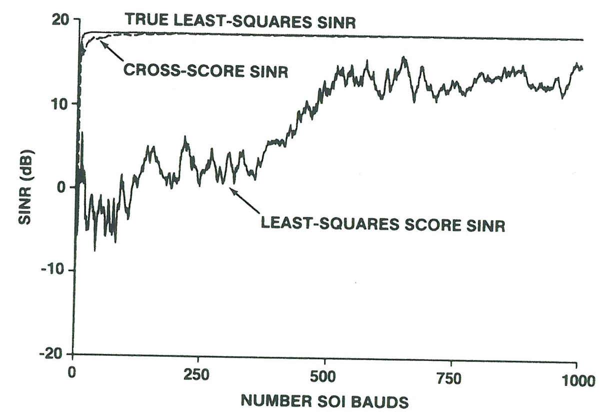

Figure 3: Carrier Restoring SCORE SINRs

6. CONCLUSIONS

A new class of algorithms for blind adaptation of antenna arrays, the *self-coherence restoral* or *SCORE* algorithms, have been introduced. Two SCORE algorithms, the *least-squares SCORE algorithm* and the *cross-SCORE algorithm* have been developed, analyzed and simulated. It has been analytically shown that a SCORE-adapted antenna array will converge to the maximum-SINR solution when a single SOI with self-coherence at a known value of frequency separation and arbitrary noise and interference without self-coherence at that frequency separation are received by the array. These results have been verified via computer simulation for a four-element circular antenna array excited by white noise, a BPSK SOI and strong tonal and MSK interferers, and adapted using the least-squares SCORE and cross-SCORE algorithms. The output SINR of the least-squares SCORE processor was shown to converge to within 3 dB of the maximum attainable SINR in 1000 SOI bauds, using only the knowledge of the baud-rate or carrier frequency offset. This convergence time was improved to 100 SOI bauds and 10 SOI bauds, respectively, when the baud-rate restoring and carrier-restoring cross-SCORE algorithms were used to adapt the antenna arrays.

These results motivate continued investigation and development of this new class of adaptive algorithms. Additional analysis is needed to determine the convergence characteristics of these algorithms. Additional work is also required to determine the behavior of these algorithms in environments containing far-field multipath (e.g., in ground-based cellular telephone systems), or in environments containing multiple independent signals with self-coherence at the same value of frequency separation (e.g., in multiple-access communication systems). Development of efficient algorithms for optimizing the cross-SCORE objective function is also a topic of immediate concern.

REFERENCES

[1] L. J. Griffiths, "A Simple Adaptive Algorithm for Real-Time Processing in Antenna Arrays," *Proc. IEEE*, Vol. 57. Oct. 1969

[2] J. G. Proakis, "Advances in Equalization of Intersymbol Interference," *Advances in Communications Systems*, ed. by A. V. Balakrishnan, A. J. Viterbi, N. Y. Academic Press, 1975

[3] W. A. Gardner, *Introduction to Random Processes with Applications to Signals and Systems*, Macmillan Publishing Company, NY, 1986

[4] W. A. Gardner, *Statistical Spectral Analysis: A Nonprobabilistic Theory*, Prentice-Hall, Englewood Cliffs, NJ, in press

[5] B. G. Agee, "The Property Restoral Approach to Blind Adaptive Signal Extraction," University of California, Davis, CA, in preparation (Doctoral Dissertation)

[6] S. V. Schell, "Self-Coherence Restoral (SCORE): A New Approach to Blind Adaptation of Antenna Arrays," University of California, Davis, CA, December 1987 (Masters Thesis)