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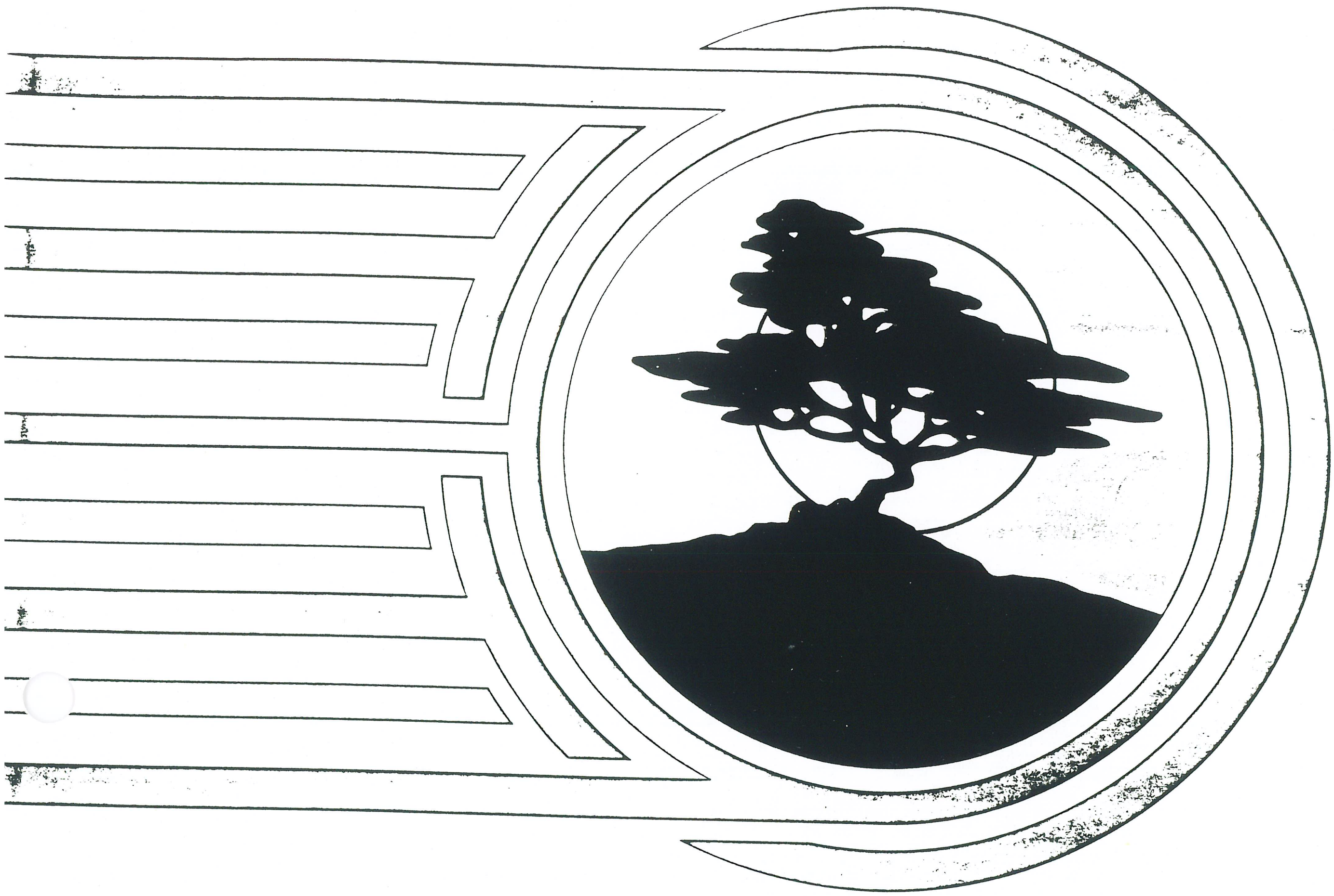

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Programmable Canonical Correlation Analysis: A Flexible Framework for Blind Adaptive Spatial Filtering*

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Abstract

In wireless communications, including cellular communication systems, spread spectrum overlay systems, and signals intelligence applications, the degradation caused by rapidly time-varying multipath and unknown co-channel interference can be reduced by adaptive spatial filtering using adaptive antenna arrays. In this paper we propose a flexible framework for adapting a spatial filter without using a training signal, array calibration data, or knowledge of spatial characteristics of the desired or interfering signals. The framework exploits one or more user-selected statistical properties to adapt the array. Simulation results illustrate the performance of algorithms developed within the new framework.

I Introduction

In such application areas as communication systems, signals intelligence, radar, sonar, commercial communications monitoring, biomedical signal processing, and geophysical exploration, signals of interest (SOIs) are often corrupted by channel distortion, interfering signals, and noise. To mitigate these sources of corruption and thus enable the receiver to obtain high-quality estimates of the SOI, it is often necessary to use adaptive spatial filtering. Conventional methods of adaptive filtering typically require prior knowledge of the SOI and/or of the corruption, such as a training signal, channel transfer function, or interference covariance matrix (cf. [1]). However, this prior knowledge can be difficult or impossible to obtain in some applications.

For example, in cellular communication systems that use time division multiple access (TDMA) (i.e., each SOI is active during only a short periodically occurring time slot) and must operate in the presence of rapidly changing multipath propagation, the characteristics of the corruption are time-varying and unknown, and periodic retransmission of a sufficiently long training signal during each time slot can decrease prohibitively the time that remains to communicate the message. Furthermore, many conventional adaptive methods are derived without regard for the statistical structure that uniquely identifies the SOIs.

The primary goal of this paper is to present a flexible framework, called Programmable Canonical Correlation Analysis (PCCA), for use in designing blind adaptive spatial filtering algorithms. The PCCA framework admits two interpretations: one is based on *canonical correlation analysis* (CCA), which is well-known in multivariate statistics (cf. [2]), and the other is based on a constrained conditional maximum likelihood problem (cf. [3]). The first interpretation is emphasized in this paper. In both interpretations, the adaptive processor contains a reference path, analogous to the path that carries the known training signal in a conventional adaptive processor; however, this reference path is derived directly from the received data by means of a user-selectable transformation. The notion of data-derived training signals is also explored in [4] for very specific signal classes. It is shown here that suitable choices of the reference-path transformation in the PCCA can allow the receiver to blindly adapt its spatial filter to separate multiple SOIs, reject interfering signals, and mitigate the effects of multipath distortion.

A more elaborate exposition of these ideas is given in [5, 6].

II Notation

In this paper, $\langle\cdot\rangle_N$ denotes the time-average over N time samples. Superscripts $*$, T, and H denote conjugation, transposition, and conjugate transposition, respectively. Symbols $\star$ and $\otimes$ denote convolution and the Kronecker product operation, respectively.

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Scalars, vectors, and matrices are denoted by lower case italic letters, lower case bold-face letters, and upper case bold-face letters, respectively. The estimate of the cross-correlation matrix between $\mathbf{x}(n)$ and $\mathbf{y}(n)$ is defined by $\hat{\mathbf{R}}_{\mathbf{xy}} \triangleq \langle \mathbf{x}(n)\mathbf{y}^H(n)\rangle_N \underset{N\to\infty}{\longrightarrow} \mathbf{R}_{\mathbf{xy}}$.

For simplicity of exposition, the complex envelope of the received data is assumed to follow the narrowband model:

$$\mathbf{x}(n) = \sum_{l=1}^{L} \mathbf{a}(\theta_l)s_l(n) + \mathbf{i}(n) = \mathbf{A}\mathbf{s}(n) + \mathbf{i}(n). \quad (1)$$

where $\mathbf{x}(n)$, $\mathbf{s}(n)$, and $\mathbf{i}(n)$ denote the complex envelopes of the received data, the signals, and the noise, respectively, and $\mathbf{a}(\theta)$ is the vector of gains and phases that describes the response of the sensor array to a plane-wave signal arriving from angle θ. In general, $\mathbf{a}(\theta)$ is a frequency-dependent function, and the ideas conveyed in this paper can be extended to this general case; an example of this extension for a particular realization of the PCCA is given in [7].

In practice, the categorization of components of $\mathbf{x}(n)$ into signals of interest (SOIs) $\mathbf{s}(n)$ and interference and noise $\mathbf{i}(n)$ is application dependent. In this paper, the SOIs are usually defined as those signals that exhibit the statistical property or properties targeted by the user-programmable reference-path transformation. However, in some cases some post-processing of the multiple signal estimates provided by the new method may be needed in order to determine which signal estimates correspond to SOIs and which to signals not of interest (SNOIs).

A class of signal transformations that is useful in this paper is referred to as the class of linear-conjugate-linear polyperiodically time-variant (LCL-PTV) transformations. In general, the output $\mathbf{y}(n)$ of such a transformation with input $\mathbf{x}(n)$ can be expressed as

$$\mathbf{y}(n) = \mathbf{W}^H \begin{bmatrix} \{\mathbf{x}(n) \star h_1(n)\}\, e^{j2\pi\alpha_1 n} \\ \vdots \\ \{\mathbf{x}(n) \star h_J(n)\}\, e^{j2\pi\alpha_J n} \\ \{\mathbf{x}(n) \star h_{J+1}(n)\}^*\, e^{j2\pi\alpha_{J+1} n} \\ \vdots \\ \{\mathbf{x}(n) \star h_J(n)\}^*\, e^{j2\pi\alpha_K n} \end{bmatrix}, \quad (2)$$

where $\mathbf{W}$ can be fixed at $\mathbf{W} = \mathbf{I}$ if desired, and $h_1(n)$, …, $h_K(n)$ are the impulse responses of linear time-invariant (LTI) filters, and α_1, …, α_K are values of frequency shifts. It is noted that the class of LTI transformations is a special subclass of the class of LCL-PTV transformations.

III The New Framework

In this section, the first of the two alternative approaches to the problem, canonical correlation analysis and constrained conditional maximum likelihood, is discussed. This approach (as well as the other) allows substantial programmability in choosing the reference-path transformations, hence the name Programmable Canonical Correlation Analysis. Several possible reference-path transformations are discussed in Section III.B.

III.A Canonical Correlation Analysis

In the canonical correlation analysis (CCA) (cf. [2]) of two data sets $\mathbf{x}(n)$ and $\mathbf{y}(n)$ that are believed to share some number L of additive components (e.g., signals) jointly denoted by $\mathbf{s}(n)$, it is desired to minimize the mean-squared error between the estimates of $\mathbf{s}(n)$ linearly obtained from each of $\mathbf{x}(n)$ and $\mathbf{y}(n)$. Denoting $\hat{\mathbf{s}}(n) = \mathbf{W}_x^H\mathbf{x}(n)$ and $\hat{\mathbf{d}}(n) = \mathbf{W}_y^H\mathbf{y}(n)$ and constraining $\mathbf{R}_{\hat{\mathbf{s}}\hat{\mathbf{s}}}(0) = \mathbf{I}$ and $\mathbf{R}_{\hat{\mathbf{d}}\hat{\mathbf{d}}}(0) = \mathbf{I}$, this can be accomplished by minimizing

$$MSE(\hat{\mathbf{s}}, \hat{\mathbf{d}}) = \left\langle \left\| \mathbf{W}_x^H\mathbf{x}(n) - \mathbf{W}_y^H\mathbf{y}(n)\right\|^2 \right\rangle_N \quad (3)$$

subject to the constraints $\mathbf{W}_x^H\hat{\mathbf{R}}_{\mathbf{xx}}\mathbf{W}_x = \mathbf{I}$ and $\mathbf{W}_y^H\hat{\mathbf{R}}_{\mathbf{yy}}\mathbf{W}_y = \mathbf{I}$.

The resulting weight matrices $\mathbf{W}_x$ and $\mathbf{W}_y$ are given by the L most dominant eigenvectors of

$$\mathbf{T}_{xy} = \hat{\mathbf{R}}_{\mathbf{xx}}^{-1}\hat{\mathbf{R}}_{\mathbf{xy}}\hat{\mathbf{R}}_{\mathbf{yy}}^{-1}\hat{\mathbf{R}}_{\mathbf{yx}} \quad (4)$$

and

$$\mathbf{T}_{yx} = \hat{\mathbf{R}}_{\mathbf{yy}}^{-1}\hat{\mathbf{R}}_{\mathbf{yx}}\hat{\mathbf{R}}_{\mathbf{xx}}^{-1}\hat{\mathbf{R}}_{\mathbf{xy}}, \quad (5)$$

respectively.

In this paper, since $\mathbf{y}(n)$ is a user-programmable transformation of $\mathbf{x}(n)$ rather than being simply another measured data set, this approach to blind adaptation is referred to as Programmable CCA (PCCA). A general block diagram of the processor is shown in Figure 1.

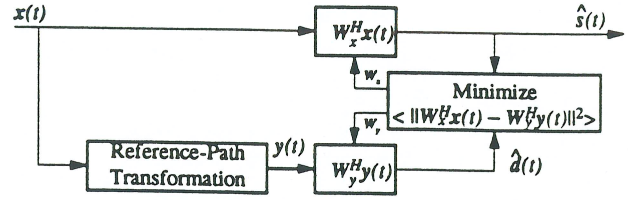

Figure 1: Generic block diagram of the PCCA adaptive processor.

III.B Reference-Path Transformations

Here a restriction on the choice of $\mathbf{y}(n)$ is discussed, and it is noted that the PCCA framework can exploit a wider variety of signal properties than just those related to cyclostationarity.

From (3) it can be seen that $\mathbf{y}(n)$ should not contain $\mathbf{x}(n)$ as a literal element, since any solution of the form

$$\mathbf{W}_y = \begin{bmatrix} \mathbf{W}_x \\ \mathbf{W} \end{bmatrix},$$

where $\mathbf{W}$ is arbitrary, would minimize (3). This observation implies that this PCCA framework cannot directly yield a blind adaptive Cyclic Wiener spatio-temporal filter, which is the optimum LCL-PTV processor (in the MSE sense) for cyclostationary signals [8].

Subject to this constraint, the objective for any particular application is to select a transformation that decorrelates the SNOI-related components in $\mathbf{x}$ from the SNOI-related components in $\mathbf{y}$, while maintaining the highest correlation between the SOI-related components in $\mathbf{x}$ and the SOI-related components in $\mathbf{y}$.

Thus, the reference-path transformation is entirely up to the user, provided that the objective (subject to the restriction) is met. To emphasize this flexibility, the *programmable canonical correlation analyzer* (PCCA) is proposed, wherein the transformation used to obtain $\mathbf{y}(n)$ is completely programmable by the user. Thus, the PCCA can use many types of signal properties to distinguish between desired signals and interference. A non-exhaustive list of transformations is proposed here:

1. $\mathbf{y}(n)$ is a frequency-shifted (by α) and delayed (by τ) version of $\mathbf{x}(n)$ or $\mathbf{x}^*(n)$, which yield the Cross-SCORE and conjugate Cross-SCORE algorithms, respectively [9]; this defines as SOIs those signals that exhibit cyclostationarity or conjugate cyclostationarity with cycle frequency α, and can be generalized to multiple frequency shifts, multiple delays, and pre-filtering.
2. $\mathbf{y}(n)$ is the output of a band-stop (or band-pass) LTI filter applied to $\mathbf{x}(n)$; this defines as SOIs those signals that have spectral support outside (or inside) the stop-band (or pass-band), and can be generalized to more complicated regions of spectral support.
3. $\mathbf{y}(n)$ is a delayed version of $\mathbf{x}(n)$; this defines as SOIs those signals for which the coherence time is greater than or equal to τ.
4. $\mathbf{y}(n)$ is the output of a temporal interval-stop (gating) device applied to $\mathbf{x}(n)$; this defines as SOIs those signals that are active outside the stop intervals.
5. $\mathbf{y}(n)$ is the narrowband (or wideband) output of an adaptive spectral-line enhancer applied to $\mathbf{x}(n)$; this defines as SOIs those signals that are relatively narrowband (or wideband).
6. $\mathbf{y}(n)$ is the enhanced (or degraded) output of a spectral-correlation enhancer (a blind adaptive LCL-PTV filter) applied to $\mathbf{x}(n)$; this defines as SOIs those signals that exhibit (or don't exhibit) cyclostationarity at a specified cycle frequency α.
7. $\mathbf{y}(n)$ is the constant modulus (or non-constant modulus) output of an LTI filter (or LTI canceller) adapted by the constant modulus algorithm (CMA) (cf. [10]); this defines as SOIs those signals that have (or do not have) constant modulus.
8. $\mathbf{y}(n)$ is the output of a demodulation-remodulation device that is applied to $\mathbf{x}(n)$ and is structured to select FM, PM, FSK, or PSK signals.
9. $\mathbf{y}(n)$ is the output of a nonlinear transformation such as $\mathbf{x}(n) \odot \mathbf{x}(n) \odot \mathbf{x}(n)$, $\mathbf{x}(n) \odot \mathbf{x}(n) \odot \mathbf{x}^*(n)$, $\mathbf{x}(n) \otimes \mathbf{x}(n) \otimes \mathbf{x}(n)$, $\mathbf{x}(n) \otimes \mathbf{x}(n) \otimes \mathbf{x}^*(n)$, or time-variant non-memoryless generalizations thereof, where $\odot$ denotes the elementwise product and $\otimes$ denotes the Kronecker product; this defines as SOIs those signals that have the higher-order stationarity or higher-order cyclostationarity properties selected for by the chosen transformation.

Examples of the first three transformations, which are specific examples of the general LCL-PTV transformation (2), are used in the computer simulations of the PCCA described in Section IV.

IV Simulation Results

Here the performance attributes of four different realizations of the PCCA spatial filter are briefly illustrated via computer simulations. In the first, second, and fourth examples, the PCCA is applied to problems in which two independent signals arrive at the sensor array, and the objective is to separate them from each other. In the third example, the PCCA is applied to a multipath mitigation problem.

In the first example, the PCCA structure is used to accelerate the convergence of the Cross-SCORE algorithm as it extracts an estimate of one BPSK signal in the presence of an interfering BPSK signal having a different baud rate. In the second example, one of the signals is replaced by a narrowband Gaussian interferer, and the reference-path transformation is simply a unit-delay. In the third example, a single SOI arrives at the array and a delayed version of the SOI arrives from a different direction; in this example, the objective is to separate the signals corresponding to the two propagation paths, and the reference-path transformation is again simply a delay. In the fourth example, the BPSK SOI and narrowband Gaussian interferer of the second example are considered again, but the reference-path transformation is simply a bandstop filter, where the stop band coincides with the spectral support of the Gaussian signal. In all of the examples, a 4-element uniform linear array having half-wavelength sensor-spacing is used, and the average output SINR is obtained by averaging the output SINRs from one hundred independent trials.

IV.A Cyclostationarity Exploitation

As shown in [3], the convergence of the Cross-SCORE algorithm (which exploits the cyclostationarity exhibited by almost all man-made communication signals) [9] can be greatly accelerated (by up to a factor of 8) by using the PCCA framework to exploit multiple cyclostationarity properties.

IV.B Delay: Signal Separation

In this simulation, the array receives a BPSK signal and a narrowband Gaussian signal. The BPSK signal has a baud rate of 0.25, zero carrier offset, 10 dB SNR, and direction of arrival of 0 degrees. The narrowband Gaussian signal consists of white Gaussian noise passed through a filter with passband $[0, 0.1]$, and arrives from 20 degrees. In the PCCA, the reference-path transformation is simply a unit-sample delay. The corresponding results are shown in Figures 2 and 3. In this simulation, the most dominant eigenvector found by PCCA extracts the Gaussian signal (because it has the longest coherence time), the next-most dominant eigenvector extracts the BPSK signal, and the least dominant eigenvectors reject the signals in favor of the noise (which, being white, is uncorrelated with the delayed version of itself, resulting in two zero eigenvalues in $\mathbf{T}_{xy}$).

IV.C Delay: Multipath Mitigation

In this simulation, a single BPSK SOI having baud rate 0.25 arrives at the array from two different directions, simulating a two-ray multipath propagation environment. Each arrival is given a random carrier phase that is uniformly distributed on $[0, 2\pi)$ radians (i.e., the phase is fixed in time but randomly chosen at each trial). The first arrival has 10 dB SNR; the second arrival has an SNR that is randomly chosen at each trial from the range 5 to 15 dB, and it is delayed by a fixed positive amount relative to the first path. The range of delays is 0.5 to 3 samples in increments of one-half sample. The reference-path transformation used by PCCA is simply a unit-sample advance, which causes the most dominant eigenvector to select the first path, whereas a unit-sample delay would cause the most dominant eigenvector to select the second (delayed) path. The output SINR for the most dominant eigenvector is shown in Figure 4, and a typical antenna pattern (obtained for multipath delay equal to one sample) shown in Figure 5 confirms that the second path is being rejected, rather than coherently combined with the first path (which would result in multipath distortion and thus adaptive post-processing would be required). As the multipath delay increases beyond the advance value used in the reference-path transformation, the output SINR decreases, which suggests that a reasonable estimate of the range of multipath delays is needed for this method to work well.

IV.D Bandstop Filtering

In this simulation, the signals are exactly the same as in Section IV.B, In the PCCA, the reference-path transformation is simply a bandstop filter that rejects the passband of the Gaussian signal. Since this also causes irreparable damage to the BPSK signal, the bandstop filter is unsuitable as the sole interference rejection device. However, it does allow the PCCA to distinguish between the signals, and thereby to reject either signal by spatial filtering alone, as demonstrated in Figures 6 and 7, which show the output SINR obtained by PCCA as a function of the number of data samples and the SNR of the Gaussian signal (which ranges from 10 dB to 50 dB). For both signals, the output SINR converges to the maximum attainable during the adaptation period considered.

Of the four spatial filters found by PCCA for this array, the two obtained from the most dominant eigenvectors reject both signals, and the least dominant eigenvector extracts the Gaussian signal, and the next-to-least dominant eigenvector extracts the BPSK signal. This ordering of the eigenvectors is predicted analytically in [6].

V Conclusions

In this paper we describe the PCCA framework and demonstrate via analysis and simulations that it is a flexible and useful framework for blind adaptive spatial filtering. In particular, the user-programmable reference-path transformation can be chosen to select signals of interest according to one or more statistical properties, such as their correlation or cyclic correlation properties, spectral support, and several others. In many cases of interest, a well-chosen reference-path transformation can enable the PCCA to converge to the same output SINR as the MMSE processor that uses a known training signal, even though the PCCA does not use known training signals, array calibration data, or knowledge of the spatial characteristics of the interference and noise. Also, when multiple signal properties are exploited in the reference-path transformation of the PCCA, significant increases in convergence rate relative to the existing Cross-SCORE method can be obtained.

Thus, PCCA gives designers of wireless communication systems and signal acquisition systems the flexibility to use other types of prior knowledge that might be more easily known in some cases, such as baud rates, carrier frequencies, temporal correlation properties, regions of temporal and/or spectral support, and so forth. In turn, the resulting capability of the PCCA to separate multiple signals of interest from each other and from interfering signals can be exploited, for example, to increase the capacity of wireless communication systems (e.g., see [11]) or to perform the blind copy operations often needed in signals intelligence operations.

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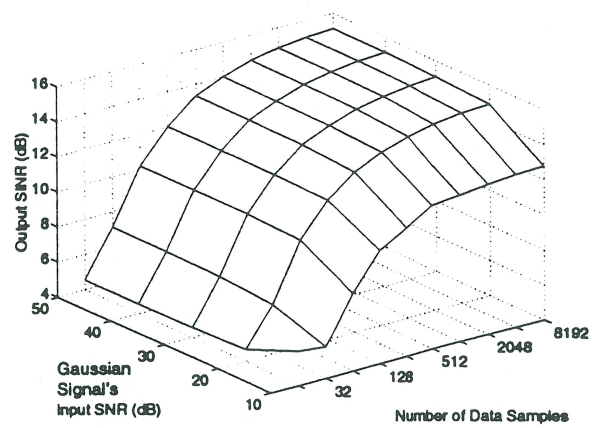

Figure 2: Output SINR for BPSK signal obtained using unit-delay reference-path transformation.

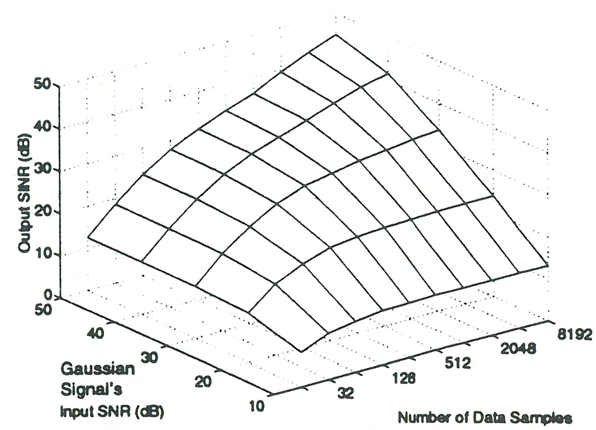

Figure 3: Output SINR for Gaussian signal obtained using unit-delay reference-path transformation.

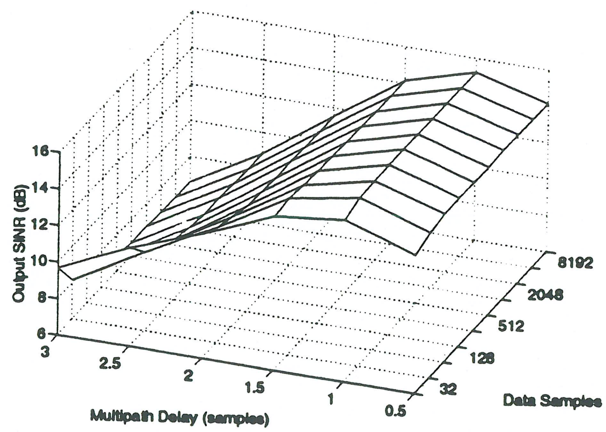

Figure 4: Output SINR for most dominant eigenvector of PCCA using a unit-sample advance to reject a multipath reflection from 20 degrees.

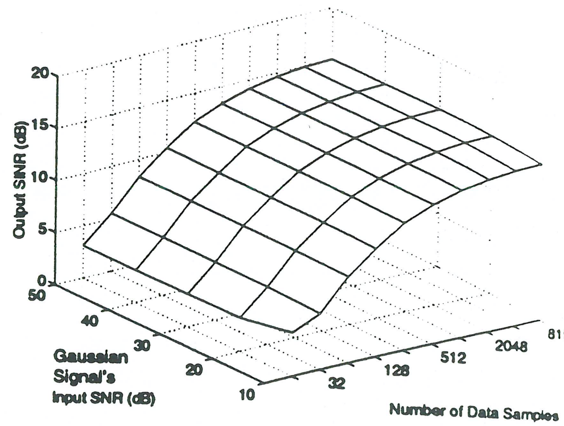

Figure 6: Output SINR for BPSK signal obtained by PCCA using bandstop reference-path transformation.

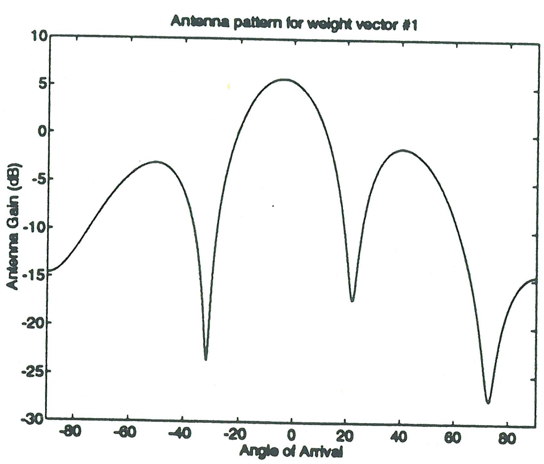

Figure 5: Typical antenna pattern showing the rejection of the multipath reflection that arrives from 20 degrees.

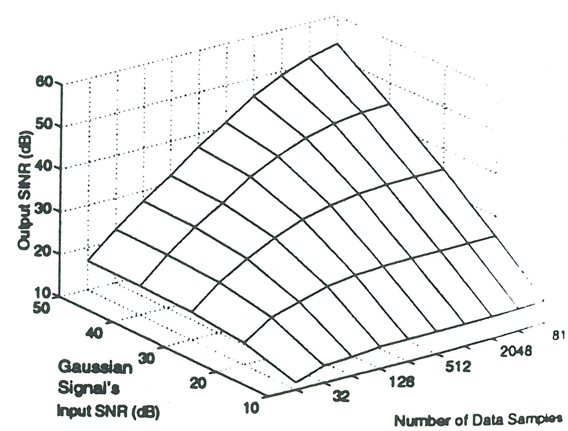

Figure 7: Output SINR for Gaussian interference obtained by PCCA using bandstop reference-path transformation.