BLIND 2-D RAKE RECEIVERS BASED ON RLS-TYPE SPACE-TIME ADAPTIVE FILTERING FOR DS-CDMA SYSTEM †

Yung-Fang Chen and Michael D. Zoltowski
School of Electrical Engineering
Purdue University
West Lafayette, IN 47907-1285
e-mail: yungfang@ecn.purdue.edu, mikedz@ecn.purdue.edu

ABSTRACT

We previously presented a blind 2D RAKE receiver for CDMA that cancels strong multi-user access interference and optimally combines multipath. The weight vector yielding the optimum signal to interference plus noise ratio for bit decisions is the "largest" generalized eigenvector of the spatio-frequency (spatio-temporal) correlation matrix pencil. However, the eigen-analysis based algorithm is on the order of $O(N^3)$ computational complexity and the resulting spatio-frequency (spatio-temporal) correlation matrix pencil is of large dimension. This detracts from the real-time applicability of that scheme. A blind 2-D RAKE receiver is thus presented based on an RLS-type space-time adaptive filtering scheme which offers $O(N^2)$ computational complexity and competitive performance. The applicability of the scheme to the IS-95 uplink is also addressed as in a decision directed fashion.

1. INTRODUCTION

In [1, 2], we presented a blind space-time processing scheme for a Direct Sequence Spread Spectrum based CDMA PCS/cellular communications system that cancels co-channel interference while simultaneously combining multipath in an optimal "RAKE-like" fashion. After passing the output of each antenna through a matched filter based on the spreading waveform of the desired user, one estimates the signal plus interference spatio-temporal correlation matrix during that portion of the bit interval where the fingers of the RAKE occur (one spatio-temporal snapshot per bit with "fingers"), and the interference alone spatio-temporal correlation matrix during that portion of the bit interval away from the fingers (multiple "away from fingers" spatio-temporal snapshots per bit). It was shown that the weight vector yielding the optimum signal to interference plus noise ratio for bit decisions is the "largest" generalized eigenvector of the resulting matrix pencil. However, even when the number of elements comprising the array is relatively small, this spatio-temporal correlation matrix pencil is of large dimension. This detracts from the real-time applicability of the scheme due to high complexity computational tasks. Specifically, these tasks are the eigen-analysis computing procedure on the order of $O(N^3)$) and estimation of the correlation matrix pencil for each processing block (outer product calculation for each snapshot). That is the motivation for this paper which considers a lower complexity scheme that offers comparable performance.

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In the previously proposed eigen-analysis based algorithms, we have $\mathbf{K}_{S+I} = \mathbf{d}\mathbf{d}^H + \mathbf{K}_I$ asymptotically, where $\{\mathbf{K}_{S+I}, \mathbf{K}_I\}$ is the space-time correlation matrix pencil and $\mathbf{d}$ is the post-correlation space-time signature of the desired user that describes the gain and phase of each RAKE finger across space and time. It can be shown:

$$\begin{aligned} SINR_{opt} &= \underset{\mathbf{w}}{\text{Maximize}} \ \frac{\mathbf{w}^H\mathbf{K}_{S+I}\mathbf{w}}{\mathbf{w}^H\mathbf{K}_I\mathbf{w}} = \mathbf{d}^H\mathbf{K}_I^{-1}\mathbf{d}, \\ \mathbf{w} &= \mathbf{w}_{opt} \propto \mathbf{K}_I^{-1}\mathbf{d} \end{aligned} \tag{1}$$

Our new RLS-based implementation is premised on the fact that MUAI's (multi-user access interference) are canceled out asymptotically by applying the weight estimated by substituting the space-time snaphshot $\mathbf{X}_{RF}(i)$ extracted from the "fingers" portion for $\mathbf{d}$. Therefore, we have the formulation of: $\mathbf{w}^{rls}(n) = \hat{\mathbf{K}}_I^{-1}(n)\hat{\mathbf{d}}(n)$, where $\hat{\mathbf{K}}_I^{-1}(n)$ and $\hat{\mathbf{d}}(n)$ are estimated adaptively by extracting those snapshots in the way described in [1, 2] such that we may consider an RLS-type algorithm to adapt $\mathbf{w}^{rls}(n)$.

2. SPACE-TIME DATA MODEL

The $M\times 1$ array snapshot vector $\mathbf{x}(t)$ containing the outputs of each of the M antennas comprising the array at time t is modeled as

$$\begin{aligned} \mathbf{x}(t) &= \sum_{k=1}^{P}\rho_k \sum_{n=0}^{N_b-1}\mathbf{a}(\theta_k^d)D(n)c(t-nT_b-\tau_k) \\ &+ \sum_{i=1}^{J}\sum_{n=0}^{N_b-1}\mathbf{a}(\theta_i)\sigma_i D_i(n)c_i(t-nT_b) + \mathbf{n}_w(t) \end{aligned} \tag{2}$$

where $\mathbf{a}(\theta)$ is the spatial response of the array. For the sake of notational simplicity, we here assume that the spatial response vector depends on a single directional parameter, θ, the direction of arrival (DOA) of a given source. However, no model is assumed for $\mathbf{a}(\theta)$ in the algorithm to be presented; the algorithm works for any array geometry. $1/T_b$ is the symbol rate common to all sources. P is the number of different paths the Signal of Interest (SOI) arrives from, θ_k^d denotes the directions associated with the k-th path, and τ_k is the corresponding relative delay of the k-th path. ρ_k is the complex amplitude of the k-th multipath arrival for the SOI at the reference element. $D(n)$ and $D_i(n)$ are the digital information sequences for the SOI and MUAI sources, respectively. J broadband interferers (MUAI) impinge upon the array. σ_i is the complex amplitude of the i-th interferer at the reference element of the array. $c(t)$ and $c_i(t)$ are the spreading waveforms for the SOI and i-th MUAI, respectively. The vector $\mathbf{n}_w(t)$ contains white noise.

N_b is the number of bits over which all parameters characterizing the model in (2) are assumed to be constant. N_b might be quite small in cases of rapidly evolving dynamics. The spreading waveform for the i-th MUAI is modeled as

$$c_i(t) = \sum_{m=0}^{N_c-1} s_i(m) p_c(t - mT_c) \quad (3)$$

where $1/T_c$ is the chip rate, $s_i(n)$ is a pseudo-noise (PN) sequence, $p_c(t)$ is the chip waveform assumed common to all sources, N_c is the number of chips per bit common to all MUAI's. The spreading waveform for the desired source, $c(t)$, is defined similarly but with a different PN sequence. The received signal at each antenna is sampled at a rate $f_s = L_c/T_c$, where L_c is the number of samples per chip. The sampled output of each antenna is passed through a filter with impulse response $h[n] = c[-n]$, where $c[n] = c(nT_c/L_c)$. For the case of a complex-valued spreading waveform as in, for example, the IS-95 uplink with QPSK spreading, we set $h[n] = c^*[-n]$.

3. RLS-BASED FORMULATION OF BLIND ADAPTIVE SPACE-TIME RAKE RECEIVER

Let $\mathbf{X}_{AF}(i,m)$ be the m-th $ML \times 1$ spatio-temporal "away from fingers" snapshot at the i-th bit period, and $\mathbf{X}_{RF}(i)$ be the $ML \times 1$ snapshot extracted from the "fingers" portion in the same manner as [1, 2], where L is the number of time samples per time window which encompass the time delay spread. Therefore, during N_b bit periods, we can form two sequences: $\{\mathbf{X}_{RF}(1), \mathbf{X}_{RF}(2), \cdots, \mathbf{X}_{RF}(N_b)\}$ and $\{\mathbf{X}_{AF}(1,1), \mathbf{X}_{AF}(1,2), \cdots, \mathbf{X}_{AF}(N_b, N_s - 1), \mathbf{X}_{AF}(N_b, N_s)\}$ which are used for estimating $\mathbf{d}$ and $\mathbf{K}_I^{-1}$respectively. For developing an RLS-type algorithm, we define the equivalence: $\mathbf{u}(n) \equiv \mathbf{X}_{AF}(i,m)$ with the relation $n = f(i,m) = (i-1)N_s + m$ for simplicity of notation, where N_s is the number of "away from fingers" snapshots extracted during a bit interval. Note that, since only one available spatio-temporal snapshot (instead of N_s) is extracted from the "fingers" portion at a bit interval, we repeat each spatio-temporal snapshot $\mathbf{X}_{RF}(n)$ N_s times with the relation:$\mathbf{v}(n) = \mathbf{X}_{RF}(\lceil \frac{n}{N_s} \rceil)$ and put the same weight on these snapshots. The following derivation closely follows [3]. We define

$$\hat{\mathbf{K}}_I(n) = \hat{\mathbf{K}}_I(i,m) = \sum_{j=1}^{n} \lambda_I^{n-j} \mathbf{u}(j)\mathbf{u}^H(j) \quad (4)$$

$$\hat{\mathbf{d}}(n) = \sum_{j=1}^{n} \lambda_d^{\lceil \frac{n-j}{N_s} \rceil} b(j)\mathbf{v}(j) \quad (5)$$

where λ_I,λ_d are the forgetting factors, $b(j)$ will be set to 1 or -1 as a state variable such that the phase of the post-correlation space-time signature of the desired user is consistent from bit to bit where it may be with 180^0 phase shift due to BPSK modulation. Initially, we set $b(n) = 1$, for $n = 1, \cdots, N_s$. For $n > N_s$ (after the first bit), we determine $b(n)$ in a differential decoding-like manner:

$$b(n) = b(n-1) \times sign(real(t(n)t(n-1)^*)) \quad (6)$$

where $t(n) = \mathbf{w}(n-1)^H \mathbf{X}_{RF}(\lceil \frac{n}{N_s} \rceil)$.

According to (4),(5), we have the following relations:

$$\begin{aligned} \hat{\mathbf{K}}_I(n) &= \lambda_I \left[\sum_{j=1}^{n-1} \lambda_I^{n-1-j} \mathbf{u}(j)\mathbf{u}^H(j) \right] + \mathbf{u}(n)\mathbf{u}^H(n) \\ &= \lambda_I \hat{\mathbf{K}}_I(n-1) + \mathbf{u}(n)\mathbf{u}^H(n) \end{aligned} \quad (7)$$

$$\hat{\mathbf{d}}(n) = \begin{cases} \lambda_d \hat{\mathbf{d}}(n-1) + b(n)\mathbf{v}(n), & \text{if } mod(n, N_s) = 1 \\ \hat{\mathbf{d}}(n-1) + b(n)\mathbf{v}(n), & \text{elsewhere} \end{cases} \quad (8)$$

Denote $\mathbf{P}(n) = \mathbf{K}_I^{-1}(n)$ and $\mathbf{k}(n) = \mathbf{P}(n)\mathbf{u}(n)$. We have

$$\mathbf{w}^{rls}(n) = \alpha(n)\{\hat{\mathbf{K}}_I^{-1}(n)\hat{\mathbf{d}}(n)\} = \alpha(n)\{\mathbf{P}(n)\hat{\mathbf{d}}(n)\}, \quad (9)$$

where the normalization factor $\alpha(n) = \frac{\sum_{j=1}^{n} \lambda_I^{n-j}}{\sum_{j=1}^{n} \lambda_d^{\lceil \frac{n-j}{N_s} \rceil}}$. After using the matrix inversion lemma and some algebraic manipulations, we have

$$\begin{aligned} \mathbf{w}^{rls}(n) &= \alpha(n)\{\alpha(n-1)\frac{\beta}{\lambda_I}\mathbf{w}(n-1) \\ &- \alpha(n-1)\frac{\beta}{\lambda_I}\mathbf{k}(n)\mathbf{u}^H(n)\mathbf{w}(n-1) + b(n)\mathbf{P}(n)\mathbf{v}(n)\} \end{aligned} \quad (10)$$

where

$$\beta = \begin{cases} \lambda_d & \text{if } mod(n, N_s) = 1 \\ 1 & \text{elsewhere} \end{cases}$$

Note that the decision variable $z(i)$ for differentially decoding the information sequence will be a sequence of $\{b(n)\}$ extracted one out of every N_s elements.

Algorithm Summary

1. *Initialize the algorithm by setting* $\lambda_I, \lambda_d \leq 1, \mathbf{P}(0) = \delta^{-1}\mathbf{I}, \mathbf{w}(0) = \mathbf{0}$, $t(0) = 1$, $\delta =$ *small positive constant,* $\alpha(0) = 1$, $S_I(0) = 0$, $S_d(0) = 0$,$i = 1$.
2. *For each sequence index,* $n = 1, 2, \cdots,$*compute*
   (a) $\boldsymbol{\pi}(n) = \mathbf{u}^H(n)\mathbf{P}(n-1)$
   (b) $\kappa(n) = \lambda_I + \boldsymbol{\pi}(n)\mathbf{u}(n)$
   (c) $\mathbf{k}(n) = \frac{\boldsymbol{\pi}^H(n)}{\kappa(n)}$
   (d) $\mathbf{P}(n) = \frac{1}{\lambda_I}(\mathbf{P}(n-1) - \mathbf{k}(n)\boldsymbol{\pi}(n))$
   (e) $t(n) = \mathbf{w}(n-1)^H \mathbf{X}_{RF}(\lceil \frac{n}{N_s} \rceil)$

   $$b(n) = \begin{cases} 1, & \textit{for } n = 1, \cdots, N_s \\ b(n-1)sign(real(t(n)t(n-1)^*)), & \textit{elsewhere} \end{cases}$$

   (f) $S_I(n) = 1 + \lambda_I S_I(n-1)$,

   $$S_d(n) = \begin{cases} 1 + \lambda_d S_d(n-1), & \textit{if } mod(n, N_s) = 1 \\ 1 + S_d(n-1), & \textit{elsewhere} \end{cases}$$

   $\alpha(n) = \frac{S_I(n)}{S_d(n)}$
   (g) $\mathbf{w}(n) =$ *Eq:(10)*
   (h) *if* $mod(n, N_s) = 0$, *decision variable* $z(i) = \mathbf{w}(n)^H \mathbf{X}_{RF}(\lceil \frac{n}{N_s} \rceil)$, *i=i+1;*

4. REDUCED DIMENSION PROCESSING

The theoretically optimum RAKE receiver requires that we sample at the multipath arrival times so that sampling 2 times per chip may not be adequate. The large dimension of the spatio-temporal correlation matrix pencil leads to a large computational burden, and requires more symbols to converge to the optimum set of spatio-temporal weights as well. These points prompted an investigation [1] into a frequency domain implementation of the RAKE receiver to achieve reduced dimensionality by selecting frequency samples around the DC component. To reduce dimensionality further, a beamspace-frequency processing scheme is proposed in [2]. In general, for processing with the reduced dimension, we design a compression matrix $\mathbf{W}_r \in \mathcal{C}^{ML \times N_r}$ which is applied to the spatio-temporal snapshot, where N_r is the dimensionality after compression. Hence, we replace $\mathbf{u}(n)$ and $\mathbf{v}(n)$ with $\mathbf{W}_r^H \mathbf{u}(n)$ and $\mathbf{W}_r^H \mathbf{v}(n)$ in the RLS-based algorithm. In the case of space-frequency processing, we have $\mathbf{W}_r = \mathbf{W}_k \otimes \mathbf{I}_M \in \mathcal{C}^{ML \times MK}$, where $\mathbf{W}_k$ is K columns of the L point DFT matrix. Practically, we implement this matrix multiplication by applying FFT to the samples in time window at each antenna output for efficiency. The beamspace-frequency version of RLS-based algorithm is still under investigation and therefore will not be discussed.

5. APPLICATION TO THE IS-95 UPLINK

The applicability of the scheme to the IS-95 uplink is addressed here such that the system would allow a looser form of power control. The transmitter block diagram for

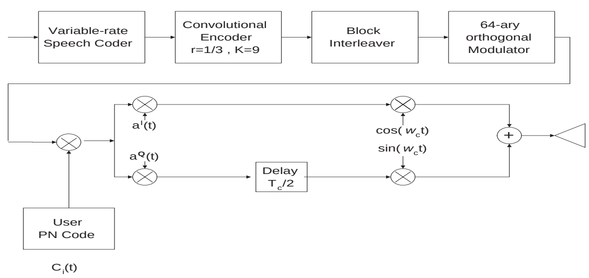

Figure 1: IS-95 Transmitter Structure for the Uplink

the uplink of IS-95 is shown in Figure 1. According to the space-time signal model used in the IS-95 uplink, we will follow the model used in [5], and therefore the discussion is omitted here. Essentially, we replace the modulation symbol and spreading waveform in classical DS-CDMA by $c_i^{(h)}(t) = W_i^{(h)}(t) a_i^{\mathbf{I}}(t) + j W_i^{(h)}(t - \frac{T_c}{2}) a_i^{\mathbf{Q}}(t - \frac{T_c}{2}), h = 1, \cdots, 64$ for user-i, where $W_i^{(h)}(t)$ denotes the h-th Walsh symbol, and $a_i^{\mathbf{I}}(t)$,$a_i^{\mathbf{Q}}(t)$ are the spreading waveform at the I and Q channels for user-i. The matched filters comprising the filters bank at the receiving end are $H_i^{(h)}[n] = c_i^{(h)*}[-n], h = 1, \cdots, 64$. We use an initialization algorithm (under investigation) or training sequence to estimate the first small number of Walsh symbols, say 3-5, such that we can select the corresponding matched filter outputs to apply the algorithm. After calculating the initial weight vector, we apply it to the matched filter bank outputs at the "fingers" portion for the next Walsh symbol period to determine which output branch contains the "fingers". At the i-th Walsh symbol period, we calculate $\hat{\mathbf{w}}^{rls}(i, N_s)$ for determining the decision statistics $z^{(h)}(i+1) = \mathbf{w}^{rls}(i, N_s)^H \mathbf{X}_{RF}^{(h)}(i+1), h = 1, \cdots, 64$ at the $(i+1)$-th Walsh symbol period, and select the output branch with the largest decision variable for updating the weight vector in a decision directed fashion [5]. We fix $b(n) = 1$ for each time instant n since the "fingers" do not flip with the orthogonal modulation in the IS-95 uplink.

6. SIMULATION RESULTS

6.1. Classical DS-CDMA

A linear array of 8 antennas equi-spaced by a half-wavelength was employed. Both the desired source and the interferers were DS-CDMA signals with different maximal length sequences and 127 chips per bit. A rectangular chip waveform was employed. The chip rate was 1 MHz

	MUAI1	MUAI2	MUAI3
SNR 1,2	-1,-11 db	-17,-15 db	-21,-24 db
Phase 1,2	$45^o, 50^o$	$-30^o, -35^o$	$180^o, 170^o$
DOA 1,2	$30^o, 35^o$	$-20^o, -23^o$	$-10^o, -7^o$
Delay 1,2 ($\times \frac{1}{2} T_c$)	$0, 3$	$0, 6$	$0, 10$

Table 1: MUAI parameters for IS-95 uplink

and the sampling rate was 2 MHz. A three-ray multipath model was used for the desired source wherein the direct path arrived at an angle of 0^o relative to broadside with an SNR of -5 dB per element. The SNR of the specular multipaths were 3 and 6 dB below that of the direct path and phase shifted by 45^o and 90^o at the first antenna element. The specular path for the SOI arrived at 3^o delayed by four and a half chips, the other arrived at 10^o delayed by seven chips. The two DS-CDMA interferers arrived at 30^o and -20^o, respectively, with power levels of 20 dB and 25 dB above the desired user's direct path, respectively. The multipath delay spread was assumed to be 8 μsec dictating sixteen half-chip spaced taps at each of the 8 antennas. The forgetting factors $\lambda_I = 1, \lambda_d = 1$ were used. The number of the spatio-temporal snapshots $N_s = 75$ were extracted in the "away from fingers" portion at each bit interval. Figures 2 and 3 show the output SINR and signal constellation of space-time RLS-based algorithm after receiving 200 bits through a static channel. Figure 4 shows a convergence rate comparison among the space-time and space-frequency eigen-analysis based algorithms, and the space-time and space-frequency RLS-based algorithm. It was observed that the SINR loss was less than 1 db after 10 bit intervals for the RLS-based algorithm compared to the respective eigen-analysis based algorithm. Also, for this simulation, the space-frequency processing offers a faster convergence rate for both the eigen-analysis and the RLS based algorithms.

6.2. IS-95 Uplink

An $M = 9$ element uniformly-spaced linear array was employed with half-wavelength spacing. Both the desired source and the interferers were CDMA signals with different long PN codes and the same short I-Q PN codes. The generating polynomials for the long and short PN sequences in [4] were used. The duration of a chip is 0.8138 μsec. A rectangular chip waveform was employed. There are 256 chips per Walsh symbol. Synchronization for the desired source was assumed (only approximate synchronization is needed in practice.) The sampling rate was two times per chip. The sliding time window was 16 samples in duration commensurate with an $\tau_{max} = 6.5 \mu sec$ multipath time delay spread. The first three Walsh symbols were viewed as a training sequence and thus were known. A simple three-ray multipath model was used for the desired user wherein the direct path arrived at an elevation angle of 0^0 relative to broadside with an SNR of -21 dB per element. The SNR of the two specular multipaths were 1dB and 3dB below that of the direct path and phase shifted by 90^0 and 45^0 at the array center, respectively. The relative delays of the specular multipaths for the desired source were $1\frac{1}{2}$ and 4 chips respectively; the elevation angles were 3^o and 10^o, respectively. The parameters for the MUAI's are listed in Table 1. We set the forgetting factor $\lambda_I = 1, \lambda_d = 0.925$ for time-varying channel. The number of the spatio-temporal snapshots $N_s = 200$ were used as the "away from fingers" portion at each Walsh symbol interval. The mobile transmitter moved toward the base station at 75 mph for the case of a time-varying channel. This induced different Doppler shift on each multipath. Figure 5 demonstrated the tracking ability of our RLS-based algorithm under rapidly time-varying

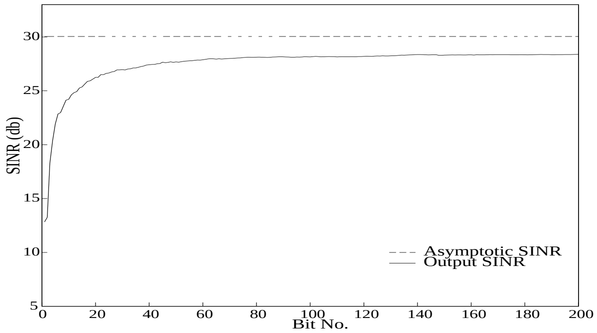

Figure 2: SINR for static channel (space-time)

channel condition. Figure 6 displays the mean (marked with x) and standard deviation (marked with o) of the decision variables at the 4-th Walsh symbol period assuming that the first 3 Walsh symbols were known. Note that we arbitrarily fix the actually transmitted Walsh symbol at 4-th symbol period to be the index 45-th for sake of illustration. The results show that the separation between the decision variable of the "true" Walsh symbol and the other 63 decision variables was approximately the same for space-time and space-frequency processing at the 4-th symbol period (note that:space-frequency processing still showed slightly higher SINR at this Walsh period in the simulation), even though the dimensionality was reduced by half and thus less computation was needed.

7. CONCLUSION

A blind 2-D RAKE receiver based on an RLS-type space-time adaptive filtering for classical DS-CDMA communication system was developed. A decision directed adaptation of the scheme was also discussed for the IS-95 uplink. Simulations reveal the scheme to be extremely promising. It provides competitive performance compared to the eigen-analysis based algorithm, and demonstrates effective tracking capabilities while a mobile moves at 75 mph, despite that the computation complexity is reduced from $O(N^3)$ to $O(N^2)$. Refinements to the scheme are under development including the convergence rate analysis, choice of initial parameters and forgetting factors and their effect on convergence rate, beamspace-frequency reduced dimension processing, and systolic array implementations.

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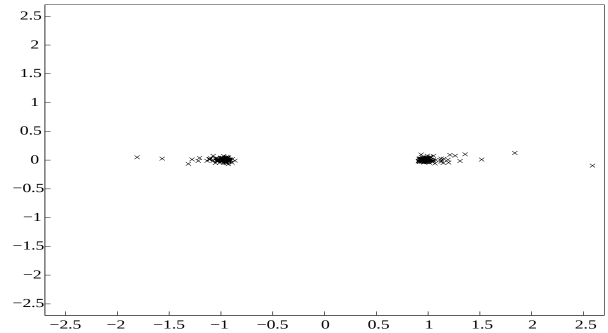


Figure 3: Signal constellation for static channel

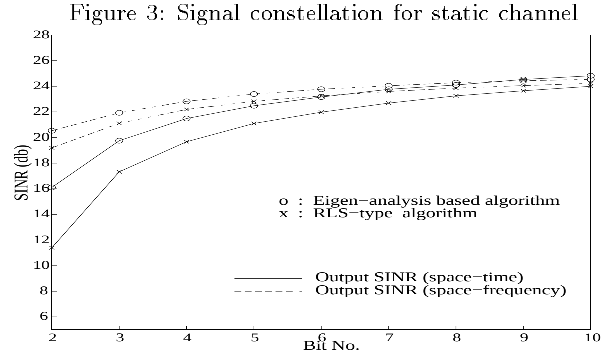


Figure 4: Output SINR comparison, mean of 128 runs

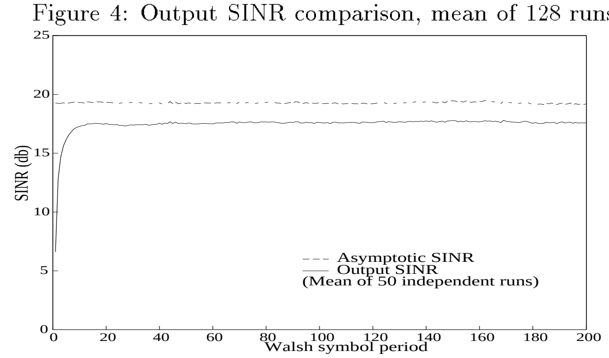
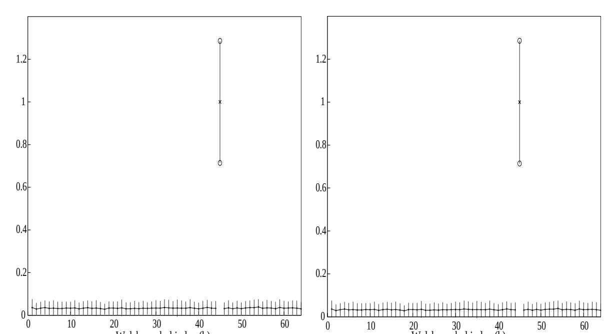


Figure 5: Output SINR (space-time) for IS-95 uplink in the case of a time-varying channel, mean of 50 runs



space-time RLS scheme space-frequency RLS scheme

Figure 6: Decision variables $\|z^{(h)}(j)\|^2, h = 1, \cdots, 64$ for the IS-95 uplink in the case of a time-varying channel, mean of 128 runs