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The Application of Blind Adaptive Antenna Arrays to Digital Wireless Communication Systems

by

Jian Cui, B.Sc., M.Sc.

A thesis submitted to
the Faculty of Graduate Studies and Research
in partial fulfillment of
the requirements for the degree of

Doctor of Philosophy

Ottawa-Carleton Institute for Electrical Engineering
Faculty of Engineering
Department of Systems and Computer Engineering
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Abstract

With the development of wireless and personal communication systems, there is considerable interest in using antenna array technology to improve the system capacity in both present and future generation wireless systems. This thesis presents a comprehensive study of the performance of a modified TDMA system which uses a combination of cyclostationary signal processing techniques and antenna arrays.

Two novel M-SCORE and PHASE algorithms are proposed for blind adaptive extraction of a signal in the presence of interference by exploiting the cyclostationarity of the received signal using an antenna array. The algorithm operates in an interference-limited system in which the desired and interfering signals have equal symbol rates, but slightly different carrier frequencies. Compared to the existing blind algorithms which also exploit the cyclo-stationarity of received signal, the new algorithms provide a simpler and faster converging means to estimate the channel phase for diversity combining. Analytical and simulation results are presented and performances are compared with DMI (direct matrix inversion), and existing blind algorithms. Based on the PHASE algorithm, a TDMA system with the new channel assignment scheme called Cyclic-TDMA (CTDMA) is proposed. The simulation results also show that the proposed PHASE algorithm is relatively simple and very promising in applications to indoor wireless communication where interference rejection and increased spectrum efficiency are the objectives. Analysis and simulation results are presented to confirm interference rejection capabilities. The robustness of existing and proposed algorithms to the perturbation of cyclostationarity and the behavior of the adaptive antenna array in the presence of a large number of interfering users is also discussed in this thesis.

This thesis presents analytical and simulation results on the output SINR (Signal to

interference plus noise ratio) of an antenna array for M elements and N interfering users in digital cellular system scenarios, including the case where $N=M$ and $N>M$. The analytical expressions are given for following three cases: i) $M=N$; ii) $M<N$; and iii) a larger number of weak interfering users are involved. The proposed approximating method present fairly close performance to the real scenarios in certain cases. Analytical and simulation results demonstrate that the output SINR of array is more sensitive to the DOA of interferer than the power of the interferer. It is also shown that by lumping interfering users into Gaussian noise gives the most pessimistic estimate of SINR performance. In case of iii), a new approximating approach is proposed for the simplicity of analysis and simulation. Simulation results show that, in practice, the output SINR of the antenna array decreases with the increase of N for fixed M even if $N<M$.

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List of abbreviations

ACI	adjcent channel interference
ADC	American digital cellular
BCF	baseband carrier frequency
BER	bit error rate
BPSK	bio-phase shift keying
C/I	carrier to interference ratio
C-CAB	constrained CAB
CAB	cyclic adaptive algorithm
CCI	co-channel interference
CDMA	code divison multiple access
CIR	channel impulse response
CMA	constant modulus algorithm
CTDMA	Cyclic-TDMA
DF	DOA finding
DFE	decision feedback equalizer
DMI	direct matrix inversion
DOA	Direction-of-arrival
DS-CDMA	direct-sequence CDMA
EGC	equal gain combining
FDMA	frequence division multiple access
INR	interference to noise ratio
i.i.d.	identical independent distribution
INR	interference to noise ratio
I^{α}NR ratio	interference after cyclic-signal processing to noise

ISI	intersymbol interference
JDC	Japanese digital cellular
LMS	least mean square
LOS	line of sight
M-SCORE	modified-SCORE
MLCE	memoryless linear combining with equalizer
MLSE	maximum likelihood sequence estimation
MLR	maximum likelihood receiver
MMSE	minimum mean square error
MRC	maximal ratio combining
$N^{\alpha}NR$	noise after cyclic-signal processing to noise ratio
OLR	optimum linear receiver
PCS	personal communication services
QPSK	quadrature phase shift keying
QAM	quadrature amplitude modulation
R-CAB	robust CAB
RLS	recursive least square
SINR	signal to interference plus noise ratio
SIO	signal of interest
SIR	Signal to interference ratio
SNR	signal to noise ratio
$S^{\alpha}NR$	signal after cyclic-signal processing to noise ratio
TDMA	time division multiple access

List of Symbols

a	-- a scale defined near equation (6.12) on page 104
$\hat{a}$	-- the project coefficient of signal (see equation (3.15) on page 33)
A	-- the unit cell area (see equation (2.12) on page 25)
A_1	-- the offered traffic per cell in erlang (see equation (2.13) on page 25)
A_0	-- DOA of desired user(see equation (3.5) on page 30)
$\hat{A}_0$	-- DOA of desired user estimated based on finite data collection (see equation (4.13) on page 48)
A_i	-- DOA of CCIs ($i = 1, 2, \dots, N$) (see equation (3.1) on page 28)
A_c	-- carried traffic per cell (see equation (2.12) on page 25)
B	-- the blocking probability (see equation (2.13) on page 25)
B_c	-- the bandwidth per channel (see equation (2.11) on page 25)
B_t	-- the total bandwidth of system (see equation (2.11) on page 25)
c	-- control vector defined in Cross-SCORE algorithm (see equation (3.19) on page 35)
$\frac{C}{I}$	-- carrier to interference ratio (see equation (2.10) on page 24)
$diag\{x\}$	-- diagonal matrix with element x (see equation (3.10) on page 31)
d	-- correlation coefficient between DOAs of two users (see equation (4.11) on page 47)
d_{ij}	-- component of a covariance matrix D (see equation (6.24) on page 108)

$d(n)$	-- training sequence used in adaptive algorithm (see equation (4.2) on page 42)
$d_i(n)$	-- the data sequence ($i = 0$ for desired user, others for CCI's) (see equation (4.5a) on page 44)
D	-- the distance between the base station of desired user to the base station of the nearest co-channel cell (see equation (2.10) on page 24)
$\mathbf{D}$	-- a matrix (see equation (6.24) on page 107)
e_i	-- a component of vector (see equation (6.25) on page 108)
$\mathbf{e}$	-- a vector (see equation (6.25) on page 108)
$e(k)$	-- an error signal defined in CAM algorithm (see equation (3.3) on page 29)
$e(n)$	-- an error signal between array output and reference signal (see equation (3.39) on page 38)
$E(x)$	-- expectation operator (see equation (4.7) on page 45)
E_s	-- system spectrum efficiency (see equation (2.12) on page 25)
$f(\lambda)$	-- the probability density function of Ricean distribution (see equation (2.1) on page 9)
$f_{\hat{p}_s}$	-- probability density function for instantaneous signal power of a Ricean variable (see equation (2.4) on page 10)
$f_{p_s}(x)$	-- probability density function for lognormal distribution (see equation (2.2) on page 10)
$F(CI)$	-- co-channel interference probability (see equation (2.5) on page 10)
$F(CI/n)$	-- the conditional co-channel interference probability for given number of active channels (see equation (2.6) on page 10)
$F_{pq}(\mathbf{w})$	-- objective function defined in CMA (see equation (3.2) on page 28)
$F_M(\theta)$	-- spatial spectrum in DOA finding method (see

	equation (3.11) on page 31)
$F_{SC}(w, c)$	-- objective function defined in Cross-SCORE algorithm (see equation (3.20) on page 35)
$\tilde{F}_{SC}(w)$	-- objective function defined in Auto-SCORE algorithm (see equation (3.29) on page 36)
$g_i(\phi_i)$	-- normalized power gain for directive antenna pattern (see equation (5.9) on page 97)
$h(t)$	-- channel impulse response of the indoor radio channel (see equation (2.7) on page 11)
$\hat{i}(n)$	-- a component uncorrelated with signal $s(n)$ and interference $i(n)$ (see equation (3.15) on page 33)
$\mathbf{I}$	-- a M by M unit matrix (see equation (3.4) on page 29)
$\mathbf{I}_M$	-- a unit matrix with dimension M by M (see equation (3.8) on page 30)
$I_0(x)$	- the modified Bessel function of the first kind and zeroth order (see equation (2.1) on page 9)
J	-- objective function defined in equation (3.38) on page 38
L	-- the memory length of channel impulse response (see equation (2.7) on page 11)
m	-- channel capacity (see equation (2.11) on page 25)
m_{TDMA}	-- channel capacity in TDMA system (see equation (5.7) on page 90)
m_{CTDMA}	-- channel capacity in CTDMA system (see equation (5.8) on page 90)
m_d	-- the mean of lognormal distribution (see equation (2.4) on page 10)
$\mathbf{n}(n)$	-- noise vector defined in array (see equation (3.1) on page 28)
$n_j(n)$	-- a component of noise vector (see equation (4.5c) on page 44)
P_d	- the instantaneous signal power (see equation (2.1) on page 9)

$\bar{p}_d$	-- the mean of instantaneous signal power (see equation (2.1) on page 9)
$p_n(n)$	-- probability of n co-channel interferes being active (see equation (2.5) on page 10)
P_i	-- the mean powers of users ($i = 0$ for desired user and others for CCIs) (see equation (3.4) on page 29)
P_{ij}	-- mean power related to fading on i th and j th channel (see equation (4.46) on page 57)
P	-- projection matrix (see equation (6.2) on page 102)
$\bar{P}$	-- complementary projection matrix (see equation (6.7) on page 103)
$P(k)$	-- inverse covariance matrix at k th moment (see equation (4.59) on page 60)
$P(\theta)$	-- antenna pattern at the specific angle (see equation (3.11) on page 31)
Q	-- matrix with DOAs of CCIs as its column vectors (see equation (6.6) on page 103)
$SINR(w_{DMI})$	-- SINR for DMI algorithm (see equation (4.34) on page 53)
$SINR(w_{M-SCORE})$	-- SINR for M-SCORE algorithm (see equation (4.34) on page 53)
r	-- signal magnitude defined in equation (2.1) on page 9
$r(n)$	-- a reference signal defined in adaptive algorithm (see equation (3.19) on page 35)
$r_i(n)$	-- a reference signal by selecting the received signal on i th antenna element as a reference (see equation (4.43) on page 55)
$\hat{r}_{xd}(k)$	-- cross-correlation vector between the received signal vector and training sequence based on finite data collection (see equation (4.56) on page 60)
$\hat{r}_{xd}(n_{\text{est}})$	-- cross-correlation vector between the received signal vector and the estimate signal based on

	finite data collection (see equation (4.71) on page 63)
r_{xr}	-- cross-correlation vector between the received signal vector and reference signal based on finite data collection(see equation (4.8) on page 45)
R	-- radius of a cell (see equation (2.10) on page 24)
R	-- a covariance matrix of received signal when $M < N$ (see equation (6.16) on page 106)
R_1	-- a interference plus noise covariance matrix when $M < N$ (see equation (6.21) on page 107)
R_2	-- a interference plus noise covariance matrix by treating the weak CCIs as noise (see equation (6.31) on page 109)
R_d	-- Ricean factor (see equation (2.1) on page 9)
R_{00}^α	-- cyclic-autocorrelation coefficient of desired user at frequency α (see equation (3.17) on page 34)
R_1^α	-- cyclic-cross-correlation vector at frequency α between the received signal and reference by selecting the signal on 1st antenna element as reference (see equation (4.41) on page 55)
$R_i^{2f_1}$	-- cyclic-cross-correlation vector at frequency $2f_1$ between the received signal and reference by selecting the signal on i th antenna element as reference (see equation (4.44) on page 57)
$\hat{R}_{11}^\alpha$	-- cyclic-autocorrelation coefficient of 1st cochannel interference at frequency α based on finite data collection (see equation (4.25) on page 51)
R_{i1}^α	-- first component of cyclic-cross-correlation vector (see equation (4.48) on page 58)
R_{ii}^α	-- cyclic-autocorrelation coefficient of i th cochannel interference at frequency α based on finite data collection(see equation (3.17) on page 34)
R_{nn}	-- interference plus noise covariance matrix (see

	equation (4.12) on page 47)
R_{nn}^{α}	-- cyclic-interference plus noise covariance matrix (see equation (3.17) on page 34)
$\hat{R}_{nn}^{\alpha}$	-- cyclic-interference plus noise covariance matrix based on finite data collection (see equation (4.25) on page 51)
R_{rr}	-- covariance matrix of reference signal (see equation (3.22) on page 35)
$R_{ss}(0)$	-- correlation function of scale signal $s(n)$ at lag 0 (see equation (3.12) on page 33)
$R_{ss}^{\alpha}(\tau)$	-- cyclic-correlation function of scale signal $s(n)$ at lag τ (see equation (3.12) on page 33)
R_{uu}	-- covariance matrix of control vector (see equation (3.22) on page 35)
R_{xu}	-- covariance matrix of received signal and control signal (see equation (3.22) on page 35)
R_{xx}	-- covariance matrix of received signal (see equation (3.4) on page 29)
$\hat{R}_{xx}$	-- covariance matrix of received signal based on finite data collection (see equation (4.13) on page 48)
$\hat{R}_{xx}(k)$	-- covariance matrix of received signal at k th moment based on finite data collection (see equation (4.56) on page 60)
R_{xx}^{α}	-- cyclic-covariance matrix of received signal (see equation (3.17) on page 34)
$\hat{R}_{xx}^{\alpha}$	-- cyclic-covariance matrix of received signal due to the perturbation of cyclostionarity (see equation (4.73) on page 65)
$\tilde{R}_{xx}^{\alpha}$	-- cyclic-covariance matrix of received signal based on finite data collection (see equation (4.17) on page 49)
$\bar{R}_{xx}^{\alpha}$	-- symmetrical cyclic-covariance matrix of received signal based on finite data collection (see equation (3.29) on page 36)

$\hat{R}_{xx}^u(k)$	-- cyclic-covariance matrix of received signal based on finite data collection (see equation (4.66) on page 62)
R_{yr}	-- covariance matrix of array output and reference signal (see equation (3.22) on page 35)
R_{yy}	-- covariance matrix of array output (see equation (3.22) on page 35)
s	-- the peak value of the direct path signal in Ricean distribution (see equation (2.1) on page 9)
$s_i(n)$	-- the data sequence ($i = 0$ for desired user and others for CCI's) (see equation (3.1) on page 28)
t_d	-- a rms delay spread (see equation (2.7) on page 11)
$u(n)$	-- control signal vector in Cross-SCORE algorithm (see equation (3.22) on page 35)
U	-- eigen-decomposition matrix with right eigenvector as its column vector (see equation (4.17) on page 49)
u_k	-- a right eigenvector (see equation (4.17) on page 49)
V	-- a eigen-decomposition matrix with left eigenvector as its column vector (see equation (4.17) on page 49)
v_k	-- a left eigenvector (see equation (3.7) on page 30)
V_s	-- a eigen-decomposition matrix with eigenvectors corresponding to signal and interference as its column vectors (see equation (3.10) on page 31)
$\hat{V}_s$	-- a estimate eigen-decomposition matrix with eigenvectors corresponding to signal and interference as its column vectors (see equation (4.34) on page 53)
V_n	-- a eigen-decomposition matrix with eigenvectors corresponding to noise as its column vectors (see equation (3.10) on page 31)
$\hat{V}_n$	-- a estimate eigen-decomposition matrix with eigenvectors corresponding to noise as its

	column vector (see equation (4.34) on page 53)
w_i	-- a component of weighting vector w (see equation (3.1) on page 28)
w	-- weighting vector (see equation (3.1) on page 28)
$w(k)$	-- weighting vector at k th moment (see equation (3.3) on page 29)
$\hat{w}(k)$	-- estimate weighting vector at k th moment (see equation (4.66) on page 62)
w_0	-- optimum weighting vector which is orthogonal to vectors A_i ($i = 1, 2, \dots, M-1$) (see equation (6.9) on page 104)
w_{CAB}	-- optimum weighting vector in CAB algorithm (see equation (3.33) on page 37)
w_{C-CAB}	-- optimum weighting vector in C-CAB algorithm (see equation (3.35) on page 37)
$\hat{w}_{DMI}$	-- optimum weighting vector in DIM algorithm based on finite data collection (see equation (4.32) on page 52)
w_{egc}	-- optimum weighting vector in sense of equal gain combining (see equation (4.50) on page 58)
w_{mrc}	-- optimum weighting vector in sense of maximal ratio combining (see equation (4.48) on page 58)
$\hat{w}_{M-SCORE}$	-- optimum weighting vector in M-SCORE algorithm based on finite data collection (see equation (4.19) on page 49)
w_{MSE}	-- optimum weighting vector in sense of minimal mean square error (see equation (4.9) on page 45)
w_{opt}	-- optimum weighting vector in sense of MMSE or SINR (see equation (3.5) on page 30)
$\hat{w}_{opt}$	-- estimate optimum weighting vector in sense of MMSE or SINR (see equation (4.13) on page 48)
$\hat{w}_P(k)$	-- estimate optimum weighting vector in PHASE algorithm (see equation (4.62) on page 61)
w_{SC}	-- optimum weighting vector in SCORE algorithm

	(see equation (3.21) on page 35)
$\hat{\mathbf{w}}_{SCORE}$	-- estimate weighting vector in SCORE algorithm (see equation (4.26) on page 51)
$\hat{\mathbf{w}}_T(k)$	-- weighting vector of two-mode algorithm (see equation (4.70) on page 63)
x_i	-- a complex Gaussian random variable (see equation (2.8) on page 11)
$x(n)$	-- scalar signal (see equation (3.15) on page 33)
$\mathbf{X}$	-- matrix with $\mathbf{A}_i$ as its column vector ($i=M, M+1, \dots, N$) (see equation (6.17) on page 106)
$\mathbf{X}(n)$	-- received signal vector at n th moment (see equation (3.1) on page 28)
$X_i(n)$	-- received signal on i th antenna element at n th moment (see equation (3.1) on page 28)
y_i	-- a complex Gaussian random variable (see equation (2.8) on page 11)
$y(n)$	-- output of antenna array at n th moment (see equation (3.2) on page 28)
$\mathbf{Y}$	-- matrix with eigenvectors of $\mathbf{R}_{xx}$ as its column vectors (see equation (3.7) on page 50)
α	-- the specified protection ratio (see equation (2.6) on page 10)
$\hat{\alpha}$	-- the perturbed cyclostationarity of received signal (see equation (4.73) on page 65)
α_i	-- a random variable (see equation (2.7) on page 11)
α_{ij}	-- real i.i.d. random variables with Rayleigh distribution ($i = 1, 2, \dots, M$; and $j = 0, 1, \dots, N$) (see equation (4.5b) on page 44)
γ	-- Lagrange multiplier for a constraint in R-CAB algorithm (see equation (3.37) on page 37)
γ_i	-- weighting coefficient on i th antenna branch (see equation (4.48) on page 58)
$\hat{\gamma}_i(k)$	-- estimate weighting coefficient on i th antenna branch at k th moment (see equation (4.62) on

	page 61)
$\Delta\alpha$	-- change in frequency offset due to the perturbation of cyclostationarity (see equation (4.73) on page 65)
ΔR_{xx}^u	-- change in cyclic-autocorrelation matrix due to the perturbation of cyclostationarity (see equation (4.73) on page 65)
Δw_1	-- change in optimum weighting vector of M-SCORE algorithm due to finite data collection (see equation (4.32) on page 52)
Δw_2	-- change in optimum weighting vector of Auto-SCORE algorithm due to finite data collection (see equation (4.33) on page 52)
$\Delta \hat{w}_{DMI}(k)$	-- change in optimum weighting vector of DMI algorithm at k th moment in tracking process (see equation (4.69) on page 63)
$\delta(x)$	-- Dirack function (see equation (2.7) on page 11)
θ_i	-- random variable with uniform distribution in $[-\pi, \pi]$ (see equation (2.7) on page 11)
θ_{ij}	-- random phase variables $\{i=1,2,\dots \text{ and } j=0,1,\dots,N\}$ with uniform distribution over the range $[0, 2\pi]$ (see equation (4.5b) on page 44)
λ	-- eigenvalue associated with eigenequation (see equation (3.26) on page 35)
λ_k	-- k th eigenvalue associated with k th eigenvector (see equation (3.6) on page 30)
λ_{max}	-- maximum eigenvalue (see equation (3.33) on page 37)
ρ	-- correlation coefficient between DOAs of desired and interfering users (see equation (6.36) on page 121)
ρ^2	-- a equivalent power by lumping weak CCI's as AWGN (see equation (6.32) on page 110)
ρ_{ss}^u	-- cyclic-correlation coefficient of scalar signal $s(n)$ (see equation (3.12) on page 33)

$\rho_{ss}^{\alpha}(\tau)$	-- cyclic-correlation coefficient of scalar signal $s(\cdot)$ at lag τ (see equation (3.12) on page 33)
ρ_{yy}^{α}	-- cyclic-correlation coefficient of array output $y(n)$ (see equation (3.27) on page 36)
$\bar{\rho}_{yy}^{\alpha}$	-- symmetrical cyclic-correlation coefficient of array output $y(n)$ (see equation (3.29) on page 36)
Σ	-- diagonal matrix with eigenvalues as its components (see equation (3.7) on page 30)
Σ_s	-- diagonal matrix with eigenvalues associated with signal plus interference as its components (see equation (3.10) on page 31)
$\hat{\Sigma}_s$	-- diagonal matrix with eigenvalues associated with signal plus interference as its components based on finite data collection (see equation (4.34) on page 53)
Σ_n	-- diagonal matrix with eigenvalues associated with noise as its components (see equation (3.10) on page 31)
$\hat{\Sigma}_n$	-- diagonal matrix with eigenvalues associated with noise as its components based on finite data collection (see equation (4.34) on page 53)
σ^2	-- noise power (see equation (2.2) on page 10)
σ_d	-- logarithmic standard deviation of lognormal distribution (see equation (2.4) on page 10)
$\phi(k)$	-- multipath power profile at k th moment (see equation (2.9) on page 11)
$\langle \quad \rangle_N$	-- a time average operation over N samples (see equation (3.2) on page 28)

Chapter 1. Introduction

The remarkable growth in the cellular radio communications over the past decade clearly illustrates the eagerness of humans to communicate on the move. However, mobile cellular telephone systems in some large cities are currently congested to near capacity[1]. The trend toward an increased demand for mobile services is expected to continue [2,3,4]. In order to meet the requirement of future cellular communication systems and to support many mobile users within a limited radio bandwidth in a given service area, it is imperative to increase the spectrum efficiency.

Cellular radio systems [5] improve the spectrum efficiency by introducing the concept of frequency reuse. This refers to the use of radio channels on the same carrier frequency to cover different areas which are separated from one another by sufficient distances so that co-channel interference does not degrade communications. Microcellular radio systems further increase the spectrum efficiency by more extensive frequency reuse to meet the growing demand for personal communication. The price paid for an increased capacity obtained from the microcell approach is more frequent handoffs.

A number of second generation systems [6] are currently being installed in several countries. All of them employ digital voice transmission. The evolving digital TDMA (time division multiple access) cellular standards in Europe (the pan-European GSM), North American (ADC, American Digital Cellular), and Japan (JDC, Japanese Digital Cellular) will give important capacity improvements and may satisfy many of the improvements needed for personal communication [7]. However, being optimized for voice transmission and with limited capacity for other kinds of information, second generation systems will still satisfy only a limited number of portable communication needs. Moreover, it is expected [8] that, by the year 2000, the demand for wireless communications will exceed the capacity of second generation technology. It is therefore a challenge to provide universal, personal and wireless access to offer to a variety of advanced information services using a limited spectrum.

In cellular radio systems, the spectrum efficiency can also be increased through the

use of digital technology employing CDMA (code division multiple access) systems. For a given coverage area, TDMA or CDMA is an option to be used as the spectrum assignment scheme in the future cellular communication system. It has been a long debate as to which scheme is better. Considering real scenarios, such as the propagation conditions and the sensitivity to power control, TDMA and CDMA can offer the same performance [9,10]. For example, [11] shows that a TDMA system with slow frequency hopping and a reuse factor of 1 can obtain capacity similar to DS-SS-SSMA. In this thesis, our research attention focuses on the TDMA option.

It is clear that third generation mobile and portable communication systems will be designed to provide a large number of high speed services such as good quality voice, high speed data, and image. In this context, the wireless system will be mainly affected by frequency-selective fading, lognormal fading (shadowing), and co-channel interference. Great efforts have been made on how to combat fading and interference with the aid of diversity and equalization techniques. Antenna arrays provide a very useful means of greatly improving the spectral efficiency by reducing the CCI (co-channel interference) and combating the effect of fading [12 - 20]. It is also well known that equalization techniques can be used to combat the ISI (intersymbol interference) due to multipath propagation time delay spread by exploiting the inherent multipath diversity of the channel.

Conventional techniques with antenna array and equalizer require prior knowledge of user data (such as training sequence, CIR (channel impulse response), DOA (direction-of-arrival), and so on) to track the changes in the communication environment. This prior knowledge sometimes is hard or too expensive to obtain. For example, periodic retransmission of a sufficiently long training signal during each time slot (for a TDMA system) can prohibitively decrease the time available for message transmission [17]. On the other hand, some systems, such as DECT [21] and the radio uplink in PACS/WACS [22,23] do not incorporate training sequence. In this thesis, we propose blind algorithms based on cyclostationary signal properties to extract the desired signal from the received signal which is distorted by the channel and corrupted by the noise and interference. The advantage of a blind algorithm is that it can achieve the close performance as a non-blind

algorithm does without reducing the spectrum efficiency.

1.1 The thesis contributions

The motivation of this thesis is to propose a novel blind algorithm which can be applied to the digital cellular environment with flat fading channel. This thesis presents a comprehensive study of the performance of a modified TDMA system which uses a combination of cyclostationary signal processing techniques and antenna arrays. The major modification to the transmitted signal format is the application of a different and small frequency offset to the carrier frequency of each interfering signal. The major contributions are as follows:

1. A new blind algorithm called M-SCORE has been proposed. It is shown that the SCORE [17] and M-SCORE algorithms give performance similar to that of Direct Matrix Inversion (DMI) [24] algorithm if the data collection time goes to infinity. Furthermore, for finite data collection, the specific formula (4.37) of signal to interference plus noise ratio (SINR) has been derived for the case of one user and one dominant interferer. The formula shows that the number of elements in the array, the input signal to noise ratio (SNR), the signal to interference ratio (SIR) after cyclic-correlation operation, and the correlation coefficient between the DOA vectors of user and interference, are the significant performance influencing parameters.
2. A novel simple and fast blind algorithm called PHASE to estimate the channel phase generalizes the idea developed in the least square SCORE algorithm [17] to a new signal modulation scheme, and provides a more accurate means of channel estimation for finite data collection than the SCORE algorithm.
3. Comparison between the DMI with training sequence and the blind PHASE algorithm shows some insights into the trade off between the spectrum efficiency and adaptation time in a variety of system scenarios.
4. Investigation is conducted in a low SINR situation, on how an array can extract the desired signal and reduce the interference to a reasonable level by the blind algorithm, so that the channel estimation and equalization can be carried out effectively in order to improve the system performance.

5. A two mode algorithm is proposed to speed up the convergence rate of PHASE for practical application. In this algorithm, PHASE algorithm is used to start the adaptation. After SINR reaches to a certain point, LMS or RLS is used to continue the adaptation process with the decision feedback mechanism.

6. A new spectrum assignment scheme called Cyclic-TDMA (CTDMA) is proposed. Under real propagation conditions including Rayleigh fading plus lognormal fading, and six interferences from the first tier and twelve interferences from the second tier for different lognormal variations, the system performance in terms of outage probability was simulated. Comparisons with the conventional TDMA were made to show that the new scheme will improve the spectrum efficiency by either using a smaller cluster size or supporting more users.

7. Analysis and simulation results are extended to show how the cyclic correlation of a signal changes with perturbation of its frequency offset. It is also interesting to know how the perturbation of frequency offset affects the SINR of array. An upper bound is derived for a certain perturbation of cyclostationarity. The importance of this work is to provide some sense of the sensitivity of the output SINR to variations in given system parameters, such as the frequency offset among co-channel users, convergence time, and number of interfering users and so on.

8. In many papers published on antenna diversity, it is usually assumed that the number of interferers N is less than that of antenna elements M . However, in real cellular mobile scenarios, although the magnitudes of some of interfering signals will be small, it is more reasonable to assume that M is less than N . It is of interest to know how the system behaves in this case. Analysis and simulation are performed under general situation of M and N . In particular a simple approximation method is proposed to study the situation where there are a large number of users to be considered. Simulation results demonstrate that proposed method gives closer performance to the real life scenario than the performance obtained by lumping the weak interference into additive Gaussian noise.

9. A fixed sectorized antenna can be used as a means to improve the system capacity. For ideal sectorial antennas and line-of-sight transmission, the interference from other

sectors will not affect the performance in the given sector. The comparisons between the performance of the adaptive antenna array and omnidirectional antenna elements, with the fixed sectored antenna system are made to see which system gives superior performance for given propagating condition and traffic load.

The work presented in thesis should provide some insight to system designers on how to use cyclostationarity of transmission signal to improve the system performance by reducing the interference and increasing the spectrum efficiency.

1.2 The organization of thesis

The background material to the thesis is presented in next chapter. It consists of three main topics. First, the characteristic of channel in flat fading and frequency-selective fading is addressed. Diversity with the aid of antenna array and equalization techniques is reviewed in the second part. Third, a brief introduction to the evaluation of the spectrum efficiency is presented. In Chapter 3, the existing blind algorithms, such as CMA (Constant Modulus Algorithm), DOA (Directional-of-arrival) finding method, SCORE algorithm and so on, are reviewed. Some comments on these algorithms are made regarding their applications and limitations. The DMI algorithm is briefly introduced first as a reference algorithm in Chapter 4 to be compared with the algorithms proposed later. This is followed by a description of proposed M-SCORE and PHASE algorithms. Simulation results are presented in Chapter 5 to demonstrate the performance of proposed algorithms and comparisons between DMI and SCORE algorithms, TDMA and CTDMA system, and adaptive array with sectored array. A real cellular scenario including Rayleigh fading and lognormal fading, CCI from the first tier and second tier is considered by simulation. Chapter 6 indicates the behavior of antenna array when there are a large number of interfering users by analysis and simulation. Chapter 7 presents conclusions and some thoughts on future work.

Chapter 2. Background

2.1 Introduction

This chapter introduces the background material on which the work of this thesis is based. It describes the environment of a cellular system, and its influences on system performance. It reviews the channel models which are widely used in the cellular radio system analysis. It also presents the summary of literature research on techniques of combating and reducing the impacts of ACI, CCI, flat and frequency selective fading. Both antenna array and antenna array with equalization techniques are reviewed. The basic concepts about spectral efficiency evaluation that will be used in the thesis are also presented.

2.2 Cellular Radio Communications

With the development of wireless communication technology, the number of wireless systems are rapidly growing in offices, manufacturing floors, and shopping areas. Wireless communication uses space as the communication medium and is allocated only a limited spectrum. It is critical to find techniques to make full use of the limited bandwidth in order to maximize the carried traffic that can be carried [2.3].

Cellular mobile radio holds the promise of meeting the increasing demand for mobile radio services. Mobile telephone service has traditionally been expensive and cumbersome, with a grade-of-service substantially lower than that provided by fixed landline. Despite these problems, the demand for service far outstripped the available capacity in many major cities, resulting in long wait for service hook up. Modern technology has made possible a significant increase in the efficiency of mobile radio through frequency reuse and sophisticated system control. Several new high capacity digital mobile radio systems have been proposed [5.6.7.8].

Reducing the cell size is a way to increase the spectral efficiency, since the number of times that the same frequency appears in a normalized area has an inverse relation to the square of the radius. This concept, i.e., a micro-cellular system, is suitable for slow moving

personal communication terminals because handovers between the cells are infrequent. In Vehicular Mobile Cellular System (VMCS), the use of small cell size will result in an unacceptably large average number of handovers. Furthermore the decrease of the cell size complicates system implementation. There have been several significant development towards more spectral efficient schemes, such as voice coding, channel coding, and modulation [25,26,27].

The spectrum efficiency can also be increased through the use of efficient access schemes, e.g. TDMA or CDMA. For example, in the GSM system, the channel bandwidth is 200 kHz and each channel is divided into 8 time slots (TDMA) [7].

Depending to the bandwidth of each channel, there are two subclasses of TDMA schemes. One is narrowband TDMA, where the channel bandwidths are less than 1 MHz. The measurement [28] indicates that, in this case, the channel fading is almost flat. Another is wideband TDMA, where the channel bandwidths are larger than 1 MHz. The fading, in this case, is frequency-selective. Although some techniques to combat flat fading may also be used to reduce the effects of frequency-selective fading, in general, equalization techniques are needed for a wideband system.

In direct sequence CDMA (DS-CDMA) techniques, every user accesses the whole bandwidth of the system and is assigned a separate access code which is designed to be orthogonal or nearly orthogonal with all other codes. Recently, there has been much interest in the use of CDMA for mobile radio. This has been mainly motivated by the work [29] in which it is claimed that CDMA may provide substantial capacity improvement over TDMA or FDMA. However, the capacity of a CDMA system has been shown to be critically sensitive to both propagation conditions and errors within the power control [10,30]. It is noted that variations in power control with standard deviations of as little as 1 or 2 dB can result in capacity decreases of 30% or more [31]. A TDMA system with random frequency hopping and re-use factor of one [11] rejects the interference in the same way as CDMA does. So far, the strategies to increase the capacity of narrowband TDMA system can result in comparable capacity performance to that claimed for CDMA systems in [29]. After all, the performance of CDMA systems depends on the ability to perform accurate

and rapid power control to minimize the co-channel interference (CCI), whereas the performance of future TDMA systems depends on the ability to reduce CCI from the adjacent cells.

The major problem caused by frequency reuse is CCI from the adjacent cells (for TDMA) and from both the desired cell and the adjacent cell (for CDMA). The system capacity is limited by the level of CCI around the desired user and the propagation conditions. Reduction of CCI, flat fading, and frequency-selective fading will increase the system capacity. Spectrum efficiency improves 16-fold (a cluster size of one) with slow frequency hopping TDMA [11].

Another powerful option to improve the spectral efficiency is to use an adaptive antenna array at the base station to combat fading and shadowing, and to reduce co-channel interference [13,32,33,34]. It results in reducing the cluster size in TDMA cellular systems. Even more improvement can be achieved [18] by exploiting the cyclostationarity in the transmitted signals without decreasing cell radius. Detailed discussion of the adaptive array with equalization techniques will be given in section 2.4.

In this thesis, we focus on the TDMA option. Only narrowband TDMA systems with flat fading are investigated with the cyclostationary signal processing method and the antenna array. A new channel assignment scheme called CTDMA is simulated and compared with a conventional TDMA system. The major objective of this thesis is to propose the blind algorithms which exploits the cyclostationary signal processing method for use in a multi-user cellular communication environment.

2.3 Channel model

2.3.1 Fast and slow fading channel

Prior to discussing the techniques used to reduce CCI, we review the propagation models used in cellular radio systems. In fact, the system capacity is not only limited by the CCI level around the user, but also by the characteristic of the channel over which the signal is transmitted. Cellular radio communications normally occur over a multipath fading channel. Due to reflections, diffraction, refractions and scattering from various structures,

a transmitted signal arrives at the receiver via multiple paths with random delays and attenuations. This multipath propagation can be characterized in the time domain by the multipath power delay profile which is essentially the average received power as a function of the propagation delay [35].

In a narrow band system, since the multipath time delay spreads are so small that all the paths can be lumped into one composite path. Therefore, the received signal at the receiver antenna is characterized by a random variable. It may follow a Rayleigh distribution, a Ricean distribution or the Rayleigh/Ricean plus the lognormal distribution. The specific random variable used in analysis will be determined by the environment of concern. The investigations in this thesis are based on the propagation results reported in [36], which states that in general, the signal fading in microcells can be decomposed into a path-loss component, together with a slow varying component having a log-normal distribution and a fast varying component with a Ricean/Rayleigh distribution. Accordingly, a three-stage propagation model should be appropriate to describe a microcellular environment: i) area mean depending on the path-loss characteristics in the range from the transmitter to the area where the receiver is located; ii) local mean within that area, which is slowly varying, and can be very satisfactorily represented by a log-normal distribution; and iii) superimposed small area power fluctuation which follows a Ricean/Rayleigh distribution for the desired signal and a Rayleigh distribution for the interfering signal.

In the microcellular radio environment, suppose the signal level r around the local mean is given by a Ricean distribution, the probability density function (pdf) of which is

$$f(r/\bar{p}_d) = \frac{r}{\bar{p}_d} \exp\left[-\frac{r^2 + s^2}{2\bar{p}_d}\right] I_0\left(\frac{rs}{\bar{p}_d}\right) \quad (2.1)$$

$$R_d = \frac{s^2}{2\bar{p}_d}; \quad p_d = (R_d + 1) \bar{p}_d$$

$$0 \leq r < \infty; \quad s \geq 0$$

where $I_0(\cdot)$ is the modified Bessel function of the first kind and zeroth order, s is the peak value of the direct path signal, $\bar{p}_d$ is the average power of the scattered signal, R_d is

the Ricean factor which depends on the ratio of the signal power from the dominant signal path relative to that of the scattered signal, and $\bar{p}_d$ is the local mean power.

The pdf for the instantaneous signal power p_d for a Ricean distribution is given by using $p_d = (1/2)r^2$

$$f_{p_d}(p_d/\bar{p}_d) = \frac{1}{\sigma^2} \exp\left(-\frac{2p_d + s^2}{2\bar{p}_d}\right) I_0\left(\frac{\sqrt{2p_d}s}{\bar{p}_d}\right) \quad (2.2)$$

The pdf for the instantaneous power of a Rayleigh random variable is

$$f(p_d/\bar{p}_d) = \frac{1}{\bar{p}_d} \exp\left(-\frac{p_d}{\bar{p}_d}\right) \quad (2.3)$$

The slow-varying local mean p_d is given by a lognormal pdf:

$$f_{\bar{p}_d} = \frac{1}{(\sqrt{2\pi}) \sigma_d \bar{p}_d} \exp\left[-(\ln(\bar{p}_d) - m_d)^2 / (2\sigma_d^2)\right] \quad (2.4)$$

Here, σ_d and $\zeta_d = \exp(m_d)$ are the logarithmic standard deviation and the area mean power of the desired signal respectively.

It is imperative to determine the co-channel interference probability for evaluating the spectrum efficiency. Co-channel interference probability is defined as

$$F(CI) \equiv \sum_n F(CI/n) p_n(n) \quad (2.5)$$

where $p_n(n)$ is the probability of n co-channel interferers being active, and $F(CI/n)$ is the corresponding conditional co-channel interference probability

$$F(CI/n) \equiv \text{Prob}\{p_d/p_n < \alpha\} \quad (2.6)$$

where p_n is the composite interference power from n active channels, and α is the specified protection ratio.

In multiple user environment analysis, when many interferences present, the total interference is given by the sum of several components, which are lognormal distributed. The sum is a random variable, which can be approximated by means of a lognormal distribution and calculated by the methods presented in [37.38].

2.3.2 Frequency-selective fading channel

Third generation mobile and portable communication systems will implement a large number of high speed services such as integrated voice and data transmission. In this context, the different high speed wideband TDMA or CDMA signals will be affected by frequency selective fading caused by multipath time delay spread. It follows that a sufficiently sophisticated receiver (e.g. using an equalizer or a RAKE receiver) can exploit the inherent multipath diversity of the transmission channel not only to overcome the detrimental effects of strong intersymbol interferences due to the channel time spreading but also to improve performance with respect to the non-dispersive case. As shown in [12.39] for the fading, non-dispersive case, the use of a space diversity scheme significantly increases the value of the capacity. In dispersive cases, as shown in [14, 15, 16, 40.41], combining the antenna array with the equalization techniques, the system capacity can be improved even more.

In indoor wireless communication, a lot of measurements have been done in order to characterize the channels. The channel model used here is presented in [42.43]. From a simulation point of view, discrete channel modeling is used, since it is more convenient as each path component of the impulse response has random amplitude and phase. The complex envelope of the impulse response of the indoor radio channel can be represented by [41]

$$h(t) = \sum_{i=1}^L \alpha_i \delta(t - it_d) \exp(-j\theta_i) \quad (2.7)$$

where the θ_i is a random variable with uniformly distribution in $\{-\pi, \pi\}$, t_d is a rms delay spread, and the α_i is a random variable with Rayleigh/Ricean or Rayleigh/Ricean plus lognormal distribution. For example, in case of Rayleigh fading, each of α_i is equal to the magnitude of the channel tap coefficient, i.e.,

$$\alpha_i = \sqrt{x_i^2 + y_i^2} \quad (2.8)$$

where x_i and y_i are the Gaussian variables with identical variances that are given by

$$\begin{aligned} \left(\frac{1}{2}\right)E[\alpha^2] &= E[x^2] = E[y_i^2] \\ &= \left(\frac{1}{2}\right)\left(\frac{\sigma_d}{2}\right)\phi((i+1)t_d) \end{aligned} \quad (2.9)$$

The variances are normalized by the path spacing, equal to the delay spread, in order to properly related the discrete representation to the continuous model delay profile $\Phi(t)$ [63] which implicitly represents paths spaced by infinitesimal intervals, i.e. where the path arrival rate is infinity. In simulations, the equation (2.7) is modified to yield average path energies whose sum is a good approximation to the area (equal to 1) under $\phi(t)$. Since the system performance is affected significantly when the delay spread is larger, it is necessary to determine the shape of the average delay profile to be used in analytical studies. A number of simple profile functions have been proposed, including the Gaussian, Uniform, 2-path, and exponential distribution profiles.

2.4 Diversity and Equalization

In mobile cellular radio communications, the performance of the system is affected by CCI resulting from frequency reuse, the ISI due to the multipath time delay spread, and the fading and shadowing due to the channel propagation characteristics between the transmitter and receiver. An antenna array provides a useful means by which the space, time, and frequency division multiple access schemes can be combined together to reduce CCI, combat the effect of fading, delay spread if small, and greatly improve the spectral efficiency [12,39,89].

It is also well known that an equalizer can be used to combat the ISI due to the multipath propagation of the desired signal by exploiting the inherent multipath diversity of the channel. The antenna array techniques are described in section 2.4.1, and some results on combining the adaptive antenna array with equalization techniques are presented in section 2.4.2.

2.4.1 Adaptive Antenna Array in flat fading

The system configuration with adaptive antenna array is shown in Figure 2.1. Several algorithms have been proposed to use an adaptive antenna array to extract signals corrupted by background noise and interference. In general, algorithms can be classified into two categories: blind and non-blind algorithms. The main difference is what reference signal or information is used by the adaptive algorithm. In the non-blind algorithm, a priori

information about the desired signals such as a training sequence or DOA (direction of arrival) of users must be known. For instance, in the DMI algorithm, a training sequence which is correlated with the desired signal is needed. However, when in some environments, information about the users is not available or it is too expensive to acquire, a blind algorithm is used. The blind algorithm tries to adapt the antenna array by using some property of the signal itself. An example of a blind algorithm is the SCORE algorithm [17].

Figure 2.1 The multiple user radio system

which uses cyclostationarity to extract the desired signal. A review of existing blind algorithms will be presented in next Chapter. Generally, non-blind algorithms have better performance and converge faster than the blind algorithms, but they require the training overhead mentioned earlier. The comparisons among the DMI, SCORE and the proposed algorithm made in Chapter 4 will provide an insight on trade off between adaptation time requirement and spectrum efficiency.

2.4.1.1. Adaptive antenna array with training sequence

In narrowband communication system (i.e., signal with flat fading), maximal ratio

combining [43] and optimum combining (MMSE combining) [13] are generally used to reduce interference and noise. With these techniques, signals received by several antennas are weighted and combined to maximize output signal to interference plus noise ratio (SINR). Thus, interfering signals are suppressed and the desired signal is enhanced. It is well known that maximal ratio combining is optimum without the CCI [45,46] and with flat fading. In mobile communications with CCI, MMSE combining is an effective way to reject the CCI [47,48]. Results show that such a system with one antenna at each mobile and M antennas at the base station can achieve either an M -fold increase in capacity (over systems without optimum combining) or tolerate $M-1$ interferences from other systems [12]. However, a training sequence is needed to estimate the DOA of desired user and to put the nulls on the DOA's of interferences.

For indoor radio communications, where the fade rate is much slower and time delay spread is smaller compared to that in an outdoor land mobile system, high speed data communication is possible with an aid of equalizer. In addition, antenna diversity combining can be implemented as an adaptive technique [48,49], so that detailed a priori knowledge of a building's radio environment is not required and changes in the environment are automatically tracked.

2.4.1.2. Adaptive antenna array without training sequence

Conventional techniques with antenna array and equalizer require prior knowledge of user data (such as training sequence, CIR (channel impulse response), DOA (direction-of-arrival), and so on) to track the change of communication environment. This prior knowledge sometimes is hard or too expensive to obtain. For example, periodic retransmission of a sufficiently long training signal during each time slot (for a TDMA system) can prohibitively decrease the time that remains to communicate the data sequence [15]. On the other hand, some systems, such as DECT [21] and the radio uplink in PACS/WACS [22,23] do not incorporate a training sequence.

When it is too expensive to use the training sequence or it is impossible to use the training sequence, a blind algorithm is preferred. Blind algorithms are developed by exploiting the properties of received data itself. A detailed discussion about the blind

algorithms will be given in next Chapter.

In this thesis, the objective is to propose blind algorithms based on cyclostationary signal properties to extract the desired signal from the received signal which is distorted by the channel and corrupted by the noise and interference. The advantage of a blind algorithm is that it can achieve performance similar to that of a non-blind algorithm without reducing the spectrum efficiency. Or the improvement in capacity outweighs the amount of spectrum to be sacrificed

2.4.2 Adaptive antenna array in frequency selective fading

In wideband systems, the ISI is another source of interference in addition to the CCI that predominates in a narrow band system. Maximal ratio combining can put up a good defence against frequency-selective fading and CCI provided that the number of antenna elements is large, depending on the time delay spread and channel bandwidth[54]. It has been shown [14] that optimum combining can also perform well in the situation of frequency-selective fading and dominant CCI if the multipath time delay is less than $0.5T$, where T is one bit duration.

Generally, the techniques used in a narrow band system may not be effectively used in a wideband system because of the ISI. Equalization techniques are necessary to reject ISI. Normally a combination of antenna array and equalizer are used [15,16,79]. The antenna array is used to combat fading and reject the interference, and the equalizer to reduce the ISI.

2.4.2.1 Equalization techniques

Much research has been done in this field. Generally, there are three types of equalizers: linear equalizer, decision feedback equalizer(DFE) and maximum likelihood sequence estimation (MLSE). Both the peak distortion criterion and the mean-square-error criterion have found widespread use in optimizing the equalizer coefficients. The DFE exhibits superior ability to equalize severe frequency-selective fading [55,56,57], specially in deep fading scenarios, than the linear equalizer does[55]. This is based on the fact that the DFE's forward filter (the structure of linear equalizer) mitigates only precursor ISI. The backward filter operating on the reconstructed data sequence thus acts to eliminate the

postcursor ISI.

For all equalizer structures proposed, as long as the total delay spread is no larger than the forward filter length, the resulting performance is found [55, 14] to be superior to the flat fading case for given SIR. This is mainly because the equalizer can exploit the inherent channel diversity resulting from multipath fading.

In order to use the equalizer, it is necessary to estimate the channel impulse response(CIR) from the transmitter to receiver by a training sequence. Alternatively, if the training sequence is long enough, it also can estimate the parameters of the equalizer directly in the MMSE sense. The amount of interference that can be reduced by the equalizer depends on the characteristics of CIR, and accuracy in its estimation, the criterion used to determine the parameters of equalizer, the properties of the training sequence, and the input SINR [58,59].

2.4.2.2 Maximum likelihood receiver (MLR)

Many works published so far assume that somehow the channel impulse response(CIR) is known exactly [14,15,16]. Under this condition, the maximum likelihood receiver shown in Figure 2.2 is the best receiver we can get, where the MLR for estimating the desired source consists of a bank of matched filters $p_{m,n}(t)$ (one filter corresponding to each source for each diversity branch, i.e. the channel impulse response), the outputs for each source being summed over all diversity branches, followed by the Viterbi Sequence estimator. A very useful bound on maximum likelihood performance — called the matched filter bound[60] is obtained under the assumptions that there is no ISI or dominant CCI, only additive noise. It also has been shown that an M-branch maximum likelihood receiver is capable of almost completely eliminating all ISI and up to M-1 dominant CCI signals[61,62]. In fact, it is difficult to analyze the performance of a maximum likelihood receiver because of its complexity. Many authors have computed matched filter bounds for various channels[40,63,64]. They have, however, almost always resorted to Monte Carlo simulation when computing BER performance over an ensemble of channels. Based on the work of Mazo[65] who analytically derived the matched filter

bound in the single-branch case with two-path Rayleigh fading channels and additive white gaussian noise, Clark[14] extends to M-branch receivers, and to the general multipath channel model.

2.4.2.3 Optimum linear receivers (OLR)

Although the MLR provides the best performance, the complexity of MLR with Viterbi algorithm grows exponentially as the channel memory increases and this may be prohibitively excessive in many applications[15,16]. Compensation for ISI is best accomplished by various equalization techniques that are far simpler to implement than the Viterbi algorithm and have proven themselves in previous applications[66,67] to be extremely effective. This is the motivation in proposing the OLR for multiple users with M-branch diversity as shown in Figure 2.3 [68,69,70]. Comparing the MLR in Figure 2.2, the transversal filter (or equalizer) replaces the Viterbi sequence estimator. Balaban and Salz[15,16] have produced the performance results for the optimum M-branch linear diversity receiver operating in digital cellular radio systems with two path Rayleigh fading channels and additive noise. They derived the optimum, in the sense of LMSE, linear equalizer-combiner structure, for a linear N th order space diversity channel with additive noise. Results also have been obtained for optimum finite-tap diversity receivers (including decision feedback ISI cancellation) operating in a variety of radio systems with and without dominant CCI [71,72,73]. Clark [14] presents the results for the optimum linear diversity receiver (MMSE criterion) that extend those of Balaban and Salz to systems with dominant CCI, and a variety of power delay profiles.

2.4.2.4 Memoryless linear combining with equalizer (MLCE)

With the combination of antenna array and equalizer in MLR and OLR, The CIR on each branch has to be estimated in order to combat fading and reject interference. Instead of using a set of matched filters on each branch, there is another way to combine the adaptive antenna array with an equalizer. The new receiver first uses memoryless combining followed by a post-combiner as shown in Figure 2.4. It has been found that the maximal power combiner with an ideal post-equalizer (i.e. the ISI can be rejected completely by equalizer) performs within 1-2 dB of the MLR, and within about 5-7 dB of

Figure 2.2 The Maximum Likelihood Receiver

Figure 2.3 The Optimum Linear Receiver

MLR with ISI (time spread delay is about one half to one bit duration)[14]. It is reported that the poor performance in ISI is partly due to maximal power combining not being optimum to combat ISI. The results also demonstrated that a simple memoryless MMSE combiner with sufficient diversity branches or sufficient degrees of freedom can combat CCI in frequency-selective fading environments.

Figure 2.4 Receiver with memoryless combining and post-combining equalization

The structure common to MLR and OLR is a set of matched-filters. In analysis, it is assumed that these filters (or CIRs) can be estimated periodically by the training sequence. In fact, many results published so far are assumed that the CIR is perfectly known, so that they focus on the issue how to combine the signals from the different antennas. In practice, the CIR estimation has to be done. However, it may not be so accurate under some scenarios. For example, the MLSE criterion implemented via the Viterbi algorithm requires the knowledge of the equivalent discrete-time channel coefficients $\{h(n)\}$. To accommodate a channel that is unknown or slowly time-varying, one may include a channel estimator connected in parallel with the detection algorithm, as shown in Figure 2.5

Figure 2.5 Viterbi Algorithm with Channel Estimator

In fact, the channel estimator is an adaptive transversal filter with the tap coefficients to be determined. The estimated information sequence at the output of the Viterbi algorithm is used in making adjustments of the channel estimator. For start-up operation, the training sequence is needed to perform the initial adjustment of the tap coefficients as is usually done in the case of the linear transversal equalizer. In an adaptive mode of operation, the receiver simply uses its own decisions to form an error signal [58].

It is seen that the channel estimation accuracy affects the performance of the system. Specifically the channel estimation error is affected by the SINR, channel characteristic, and so on. However, how the channel estimation error affects the system performance in optimum and linear combining scenarios is still not clear.

Our discussion so far is applicable to antenna diversity at the base station to improve the system performance. Those techniques are more difficult to apply to mobiles due to space and cost restrictions. In this case, basestation diversity can be used to provide diversity benefit at a receiver with multiple transmit antennas. With base station diversity, multiple antennas transmit delayed versions of a signal, creating frequency-selective

fading, which is equalized at the receiver to provide diversity gain[74,75].

2.5 Sectorized antenna array

Sectorized antennas with fixed directivity can be used to improve the capacity of cellular system by reducing the interference and time delay spread. For ideal sectorial antennas, the interferences from other sectors will not affect the performance in sector of interest. A novel “intelligent” antenna system consisting of six equal 60° directional antennas used for both transmitter and receiver was developed by Motorola [76,77]. The system achieves required signal gain by selecting receiving antenna sectors. while ensuring full signal coverage within a microcell by selecting transmitting antenna sectors. The identities of the transmitting sectors are encoded in the signals. so it can then select the combinations of transmitter antenna sector and receiving antenna sector that delivers the best signal, while blocking out all duplicate signals from other sectors. The best signal is a function of both signal strength and quality. Since the ALTAIR system is not designed to be portable, the base station and the user units are mounted at fixed angles which is suitable for on-desk communication in buildings.

Another system, in which the omnidirectional antennas are used for the portables, and antennas with three sectors for the base stations, is simulated in [130]. It is reported that this CDMA system reduces the blocking and call drop probability even at high offered loads.

With rms delay spread is typically on the order of 100 ns [35,78] in indoor environments, the maximum data rate is about 1 Mbps. When the data rate increases and a sector array can not reduce the time delay spread to the desired level, a sector array with equalization techniques has been proposed [79] to increase the data rate. Considering the propagation model using ray tracing, the work indicated that it is possible to use 6-sector antenna array with simple DFE (Decision Feedback Equalizer) to support a data rate up to 20 Mbps.

Current proposals consider equalization or multicarrier processing to increase this data rate to 20 Mbps, but the circuitry is near the complexity limit. The feasibility of indoor wireless communication at very high data is considered with a larger number of directional

antenna elements [80,81]. Experiments using a 19-GHz 622-Mbps BPSK link and 15 degree beamwidth horn antennas in an office building with plaster walls and large metallized windows have demonstrated error-free performance on both LOS and non-LOS links. Furthermore, based on the propagation-prediction techniques and verified by their experimental measurements using directive antenna (15 degree beamwidth) at both ends of a link between the center of the building to an end of building, they have shown that high-speed ubiquitous communication is feasible. Using antenna arrays with 50 to 200 elements at both the transmitter and receiver, it is expected to obtain entire floor coverage at data rates in excess of 1 Gbps.

It is worth to mention that the hybrid configuration of adaptive and sectorized array is proposed in [131] to improve system performance in the reverse link budget of CDMA cellular networks. In this system, a base station with three 120° sectors and each sector has several antenna elements. Considering a typical multipath propagation environment, they quantify the excess SINR due to smart antenna processing at the base station as a function of the number of sensors, their separation, and scattering angle.

2.6 Spectrum efficiency

Spectrum efficiency is one of the main features of any high capacity mobile radio system. Many methods have been employed in an attempt to evaluate and compare the modulations, multiple access techniques, and different communication systems in terms of their spectrum efficiency. These methods range from mathematical derivation, statistical estimations, to computer simulations.

The procedures that give a general framework for evaluating the spectrum efficiency of cellular radio systems are presented in [10,82,83] for both TDMA and CDMA systems. The comparison between analog and digital systems for FDMA, TDMA, and CDMA are made in [1,7,10,11,24,84,85]. The comparisons among the different second generation digital systems, such as the GSM, ADC, and JDC are presented in [7].

Spectrum efficiency is defined as the maximum number of calls which can be made in a given area with fixed bandwidth and fixed outage or BER performance. In most

systems. channel efficiency, the ratio of bit rate to transmission bandwidth, is directly related to spectral efficiency. However, in cellular systems where channels are reused over and over again, spectral efficiency is not equal to channel efficiency. Furthermore, spectral efficiency is the parameter we hope to maximize, not channel efficiency [86]. In an idealized cellular radio systems, the service area of a cellular radio system is divided into a regular array of hexagonal cells. These cells are grouped into identical clusters, each cluster is assigned the total bandwidth available for the mobile radio system.

Three frequently used factors to evaluate the spectrum efficiency are introduced in the following.

Cluster size K

The cluster size K is determined by the C/I (carrier to interference ratio) for given communication environment. If, for simplicity, only the path loss is considered, the required C/I for TDMA or FDMA systems [86] is approximately

$$\frac{C}{I} = \frac{1}{6} \left(\frac{D}{R} \right)^4 = \frac{3}{2} K^2 \quad \text{or} \quad K = \sqrt{\frac{2C}{3I}} \quad (2.10)$$

where, R is the radius of a cell. D is the distance between the base station of desired user to the base station of the nearest co-channel cell, the assumption of 4th power law is used. The cluster size is a function of the required carrier-to-interference ratio. A higher required carrier-to-interference ratio at the boundary of a cell results in the need for larger cluster size K. The pattern of reuse cells can then be determined. The above equation is the result under ideal conditions. Considering the real cellular radio system, the C/I is a random variable whose distribution is determined by the propagation conditions, the traffic load around the desired users. The C/I can be found for a given scenario by the analytical work or Monto Carlo simulation depending on the complexity of the system model used in analysis.

Number of channels per cell m (Radio capacity)

The number of channels per cell is a function of the total number of channels available (amount of available spectrum divided by channel bandwidth) and the required C/I and is given by

$$m = \frac{B_t}{B_c K} = \frac{B_t}{B_c \sqrt{\frac{2C}{3I}}} \quad \text{channels/cell} \quad (2.11)$$

where. $m \times K$ is the total number of channels. m is also called radio capacity by Lee [86]. B_t is the total bandwidth of system. B_c is the channel bandwidth.

Spectrum efficiency

Concerning the blocking probability and the service area, the radio channel capacity can be modified to give the system spectrum efficiency which is defined as

$$E_s = \frac{A_c}{m B_c K A} \quad \text{Erlang/MHz/km}^2 \quad (2.12)$$

where. m is the number of channels per cell. B_c the bandwidth per channel. K cluster size. A the unit cell area. A_c the carried traffic per cell (or maximum traffic for given blocking probability and C/I) which can be obtained by

$$A_c = A_1 (1 - B) \quad (2.13)$$

where. A_1 is the offered traffic per cell in erlang. B is the blocking probability which is determined by using the Erlang- B formula [87].

2.7 Summary

In indoor cellular radio communication, spectral efficiency is a key issue of concern. Tremendous effects have been made to improve the spectral efficiency by exploiting the modulation efficiency, multiple access schemes, diversity and equalization techniques. Recently there is a considerable interest in using antenna array as a part of future wireless communication systems [79,80,81,88, 118]. Four configurations of antenna array and antenna array with equalizer have been proposed, such as adaptive antenna arrays[88], adaptive antenna arrays with equalizer [118], sectored antenna arrays [80,81], and sectored antenna arrays with equalizer [79]. The applications of these configurations will depend on the trade off among several factors, such as, the rms time delay spread, the channel model in specific environment, the co-channel interference, and the complexity of the system.

Chapter 3. Existing Blind Algorithms

3.1. Introduction

According to the kind of information used to adapt the weight on each antenna element, all the adaptation algorithms can be classified into two main catalogues: non-blind and blind algorithms. For non-blind algorithms, such as DMI, RLS and LMS, some prior information about the desired user must be known at the receiver. Blind algorithms exploit the properties of received signal itself. In other words, the so-called blind signal estimation is one that estimates unknown source signals from the observations without explicit knowledge of the transmission channel as shown in the schematic diagram in Figure 3.1 [90].

Figure 3.1 A schematic diagram of the blind signal estimation

Recently, blind signal estimation has attracted increasing research attention [17, 18,19,20,91-103] due to its wide range of applications from mobile radio and regenerative satellite communications to array signal processing. The approaches to blind signal estimation have been categorized [17] into two groups: spatial-coherence exploitation

techniques and property restoring techniques. The spatial-coherence exploitation techniques utilize the structural information of the transmission channel. Well-known algorithms such as MUSIC [52] and ESPRIT [53] take advantage of such structural information to obtain the estimates of the parameters. Unfortunately, the structural information is not always accurate in many practical circumstances. For example, when the antenna arrays (or sensor arrays) have unknown antenna gain and phase perturbation, or there is strong cochannel interference, the structural assumptions used in MUSIC and ESPRIT are no longer valid. As a consequence, the performance of these algorithms may suffer significant degradation [104,105]. The property restoring techniques, on the other hand, capture the properties of the source signals while leaving the channel structure arbitrary. Signal properties such as low modulus variation [91] and self-coherence [17] lead to blind signal estimation algorithms for communication applications. However, the extracted signals by property restoring techniques, though optimal with respect to certain known properties of the sources, may not possess other unknown but important features of the actual sources. For example, there is often no guarantee that the signals extracted via the property restoring techniques will have the same waveform as the actual source signals [90].

Comparing with non-blind algorithms, such as DMI, RLS, that already widely are used in wireless communication system, there is no effective blind algorithm which can be universally applied to the multi-user communication scenarios. The purpose of this chapter is to review several blind algorithm, such as CMA (Constant Modulus Algorithm) [91], DOA (Direction-of-arrival) finding method [52,53], SCORE [17,20], and other algorithms [50,95,96]. The limitation of these algorithms are also discussed in details from the application point of view.

3.2. CMA

CMA (Constant Modulus Algorithm) has been proposed by Treichler and Agee [91] based on the constant modulus properties of the desired signal which is destroyed by addition of noise, co-channel interference and multipath interference. Figure 3.2 shows the

basic structure of the CMA adaptive array.

Figure 3.2. CMA adaptive array

Considering an $N+1$ users environment with M -element antenna array, suppose the signal received is

$$\begin{aligned} X(n) &= [X_1(n) \ X_2(n) \ \dots \ X_M(n)]^T \\ &= \sum_{i=0}^N s_i(n) A_i + n(n) \end{aligned} \quad (3.1)$$

where T denotes transpose. $\{s_i(n), i=0,1,\dots,N\}$ are the signals from the different users or the multipath signals from one desired user. $\{A_i, i=0,1,\dots,N\}$ are the DOAs of the users or paths, and $n(n)$ is the Gaussian noise vector.

The optimum weighting vector $w = [w_1 \ w_2 \ \dots \ w_M]^T$ is chosen by minimizing

$$F_{pq}(w) = \langle |y(n)|^p - 1 \rangle_N^q \quad (3.2)$$

where $\langle \rangle_N$ is a time average operation.

The parameters p and q affect the sensitivity and the convergence behavior of CMA

[92]. Usually, lower p and q provide higher noise tolerance and stability under slower convergence. The optimum weighting vector in recursive manner for $p=1$ and $q=2$ is of form

$$\begin{aligned} w(k+1) &= w(k) - \mu e(k) X^*(k) \\ e(k) &= y(k) - y(k) / |y(k)| \end{aligned} \quad (3.3)$$

where μ is the step constant and $*$ indicates the complex conjugate. Equation (3.3) is similar to the LMS algorithm. However, they are different in that CMA requires no reference signals for estimating the error function $e(k)$.

CMA is a blind algorithm proposed to extract the signals by exploiting the known modulus properties of the transmitted signal waveforms or symbol sequences [20]. The advantage of CMA is simple for implementation. One example is shown in [94] which implement the CMA adaptive array for high speed GMSK transmission in indoor mobile communications with noise environment. However, as shown in [20,92,93], the shortcomings of CMA are the convergence and capture characteristics, that is, there is no guarantee that CMA can capture the desired users if co-channel users are involved in communication environment. Since CMA is essentially a stochastic gradient descent, analogous to the LMS adaptive algorithm, but deals with a performance measure distinct from mean squared error. Due to the nature of the cost function (3.2), uniqueness of finite extrema cannot be guaranteed in general. Since spectral or second-order statistical information about the signals is insufficient to numerically compute optima, even in very simple contrived situations, there exists serious uncertainty about the usefulness of a gradient-based adaptive algorithm. This limits the application of CMA in mobile communication system.

3.3. DOA Finding Algorithm

Suppose there is an M -element array with $N+1$ interfering users and $M > N$, a $M \times M$ covariance matrix of received signal vector $X(n)$ in (3.1) is given by

$$R_{xx} = \langle X(n) X(n)^H \rangle_N = \sum_{i=0}^N P_i A_i A_i^H + \sigma^2 I \quad (3.4)$$

where P_i ($i=0,1,\dots,N$) are the powers of i th user respectively, and σ^2 is the noise power.

As shown in [119] that the optimum weight vector in MMSE sense is given by

$$\mathbf{w}_{opt} = \mathbf{R}_{xx}^{-1} \mathbf{A}_0 \quad (3.5)$$

where the user number 0 is treated as the desired user regardless the scale factor. Since it is not difficult to calculate $\mathbf{R}_{xx}$ from the received data, the problem to find the optimum weighting vector in (3.5) is reduced to estimation of $\mathbf{A}_0$, the direction-of-arrival (DOA) of desired user.

DOA finding (DF) is another type of blind algorithm often discussed in literature [52,53]. Instead of finding the optimum weighting vector itself, DF algorithms are proposed to estimate the DOA of desired user directly. Several DOA finding (DF) methods using signal subspace methods for DOA estimation of multiple sources [52, 53, 20, 107, 108] have been proposed. The well-known DF is MUSIC [52]. Here is the brief introduction of MUSIC algorithm.

Let $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_M$ denote $\mathbf{R}_{xx}$'s eigenvalues, then the $M-N-1$ eigenvalues of $\mathbf{R}_{xx}$ are given by

$$\lambda_k = \sigma^2 \quad k = N+2, N+3, \dots, M \quad (3.6)$$

And also let $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_M$ represent their associated eigenvectors. The $\mathbf{R}_{xx}$ can be rewritten as

$$\mathbf{R}_{xx} = \sum_{k=1}^M \lambda_k \mathbf{v}_k \mathbf{v}_k^H = \mathbf{Y} \mathbf{\Sigma} \mathbf{Y}^H \quad (3.7)$$

where

$$\mathbf{Y} = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_M], \quad \mathbf{Y}^H \mathbf{Y} = \mathbf{I}_M \quad (3.8)$$

and

$$\mathbf{\Sigma} = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 & 0 \\ 0 & \lambda_2 & \dots & 0 & 0 \\ \dots & \dots & \dots & 0 & 0 \\ 0 & 0 & 0 & \sigma^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma^2 \end{bmatrix}. \quad (3.9)$$

If we define the subspaces spanned by $\{v_1, v_2, \dots, v_{N+1}\}$ and $\{v_{N+2}, \dots, v_M\}$ as the signal-plus-interference subspace and noise subspace respectively, the covariance matrix in (21) can be rewritten as

$$R_{xx} = v_s \Sigma_s v_s^H + v_n \Sigma_n v_n^H \quad (3.10)$$

where $v_s = [v_1, v_2, \dots, v_{N+1}]$, $v_n = [v_{N+2}, \dots, v_M]$, $\Sigma_s = \text{diag}[\lambda_1, \lambda_2, \dots, \lambda_{N+1}]$, and $\Sigma_n = \text{diag}[\lambda_{N+2}, \dots, \lambda_M]$. It is noted that v_s is orthogonal to v_n .

The DOA's are estimated from the noise subspace v_n by finding the $N+1$ highest peaks of the Spatial spectrum

$$F_M(\theta) = \frac{1}{\|v_n^H P(\theta)\|^2} \quad (3.11)$$

over the θ in the range of $[0, 2\pi]$, where $P(\theta)$ is the antenna pattern at the angle of θ .

The DF algorithm of MUSIC can be summarized as following:

1. Find the null space, v_n of R_{xx} and its rank, $M-N-1$;
2. Search over θ for the $N+1$ highest peaks in $F_M(\theta)$

There are some alternate versions of MUSIC [107,108]. The disadvantages of MUSIC DF algorithms are that the number of signals of interest (SIOs) must be less than the number of elements in the array, since the freedom limitation of the array; It is needed to know the statistical characteristic of the noise in order to estimate the number of SOIs in the system. The resolution of DOA is limited by the beamwidth of the array. Furthermore, the serious problem, from the wireless communication point view, is that the DF algorithms are based on the phase information among the antenna elements. That is, we must know the antenna pattern $P(\theta)$ which is only available in case of non-fading, or the Ricean fading with significant line-of-sight path and may be applicable for PCS microcellular system. Generally, in mobile communication, the signal received is a composite signal from many paths. The gain and phase of received signal on each antenna element are random variables. In this case, there is no guarantee that the spatial spectrum of the composite DOA's of desired users has a peak at the physical direction of desired user. Consequently, it is very hard, if not impossible, to generate the pattern of antenna array to maximize the desired

signal and null the interference by the DOA finding method [20].

3.4. SCORE Algorithm

3.4.1 Introduction

A cyclostationary signal exhibits spectral coherence at the integer multiples of its fundamental periodicity such as the baud rate, chip rate or carrier frequency. Based on the cyclostationarity of transmission signal, Gardner et al [17,18,19,20,50,51] developed a series of blind algorithms called SCORE to extract the desired signal and reject the interferences. Instead of using the training sequence as the reference signal, SCORE algorithm uses the frequency-shifted version of the received signal as the reference signal to adapt the weight vector. SCORE algorithms were developed to maximize the spectral self-coherence of the signal output of an adaptive array. The resulting solution was shown to extract a spectrally self-coherent desired signal from an arbitrary interference environment provided that the interference does not exhibit spectral self-coherence at the frequency separation of interest. Theoretically, it is proven that SCORE algorithm has the same performance as that of DMI with the training sequence, if the data collection time is long enough. The SCORE algorithm can be extended to scenarios where more than one user's signals are spectrally self-coherence at a frequency separation of interest. The SCORE algorithm will blindly adapt the receiver to extract multiple spectrally self-coherent signals and also to sort the signals on the basis of their magnitudes of spectral self-coherence. Actually, the optimum solution of SCORE is a eigenvector of a certain eigenequation. The eigenvector is a linear combination of the DOA's of users. It is known [19] that, for frequency-selective fading, SCORE algorithm can only be used to extract the multipath desired signal and reject interference when the latter's periodicity is different from that of desired signal. Thus although array has some equalization function, it can not reject the ISI effectively, especially the time delay spread is large. Generally, an equalizer is needed to reduce the ISI to the required level.

In this section, the concept of spectral self-coherence is first introduced, since it plays an important role in the cyclostationary signal processing technology. After that, three

versions of SCORE algorithms, such as LS-SCORE, Cross-SCORE, and Auto-SCORE algorithms are reviewed.

3.4.2 Spectral Self-coherence

It is known that the SCORE algorithm can blindly extract a signal of interest with spectral correlation at a known value of frequency separation. A scalar signal $s(n)$ is said to be spectrally self-coherent at frequency separation α if the correlation between $s(n)$ and $s(n)$ frequency-shifted by α is nonzero for some lag τ , that is, if

$$\rho_{ss}^{\alpha}(\tau) = \frac{R_{ss}^{\alpha}(\tau)}{R_{ss}^{\alpha}(0)} \neq 0 \quad (3.12)$$

at some values of τ , where

$$R_{ss}^{\alpha}(\tau) = \frac{1}{N} \sum_{k=1}^N s\left(k + \frac{\tau}{2}\right) s\left(k - \frac{\tau}{2}\right) e^{-j2\pi\alpha k} \Big|_{N \rightarrow \infty} \quad (3.13)$$

If a signal $s(n)$ is not a spectrally self-coherent at α , the component $R_{ss}^{\alpha}(\tau)$ will be zero. Since the cyclic correlation between signals reaches its maximum value at $\tau=0$ for BPSK signal used in simulation latter on, so that $\tau=0$ is used through this thesis, and $R_{ss}^{\alpha}(0)$ is simply written as R_{ss}^{α} .

The function ρ_{ss}^{α} can be interpreted as a measure of the relative strength of $s(n)$ contained within $s(n)\exp(j2\pi\alpha n)$. Using the Orthogonal Projection Theorem [17], $s(n)\exp(j2\pi\alpha n)$ can be represented by

$$s(n) e^{j2\pi\alpha n} = \rho_{ss}^{\alpha} e^{-j\pi\alpha\tau} s(n) + \sqrt{1 - \rho_{ss}^{\alpha}} e(n) \quad (3.14)$$

where $s(n)$ and $e(n)$ are equal-power orthogonal waveforms with $R_{se}(\tau)=0$. Suppose another scalar signal $x(n) = s(n) + i(n)$, where $i(n)$ is a interference which is not spectrally self-coherent at frequency separation α . In terms of the decomposition given in (3.14), $x(n)\exp(j2\pi\alpha n)$ can be expressed as

$$x(n) e^{j2\pi\alpha n} = \hat{a} s(n) + \hat{i}(n) \quad (3.15)$$

where

$$\begin{aligned}\hat{a} &= \rho_{ss}^{\alpha} e^{j\pi\alpha\tau} \\ \hat{i}(n) &= \sqrt{1 - \rho_{ss}^{\alpha}} e(n) + i(n) e^{j2\pi\alpha n}\end{aligned}\quad (3.16)$$

and $\hat{i}(n)$ is uncorrelated with both $s(n)$ and $i(n)$. It is known that a DMI algorithm will automatically track the desired signal if it has a reference signal correlated with the desired signal and uncorrelated with noise and interference. Equation (3.15) motivates the development of interference cancellation techniques that use $x(n)\exp(j2\pi\alpha n)$ as the reference signal in a conventional least-squares algorithm.

Suppose the received signal is given by equation (3.1) and only $s_0(n)$ is spectrally self-coherent at the frequency $\alpha=2f_1$, then the cyclic autocorrelation of $X(t)$ at the frequency separation α is given by

$$\begin{aligned}R_{xx}^{\alpha} &= \frac{1}{N} \sum_{k=1}^N X(k) X(k)^H e^{-j2\pi\alpha k} \Big|_{N \rightarrow \infty} \\ &= R_{00}^{\alpha} A_0 A_0^H + \sum_{i=1}^N R_{ii}^{\alpha} A_i A_i^H + R_{nn}^{\alpha} I = R_{00}^{\alpha} A_0 A_0^H,\end{aligned}\quad (3.17)$$

where

$$\begin{aligned}R_{ii}^{\alpha} &= \frac{1}{N} \sum_{k=1}^N s_i(k) s_i(k) e^{-j2\pi\alpha k} \Big|_{N \rightarrow \infty} \\ R_{nn}^{\alpha} &= \frac{1}{N} \sum_{k=1}^N n(k) n(k) e^{-j2\pi\alpha k} \Big|_{N \rightarrow \infty}\end{aligned}\quad (3.18)$$

where H is the conjugate-transpose operator. It is noticed from (3.17) that the infinite time-averaged cyclic autocorrelation of $X(n)$ is the same as that of $A_0 s_0(n)$, which means that the SINR is improved after the cyclic-correlation operation.

3.4.3 SCORE Algorithm

Generally, there are three types of SCORE algorithms: Least-square SCORE, Cross-SCORE, and Auto-SCORE. Each of them was derived based on different objective function. A brief introduction to the three algorithms is given as follows.

Least-square SCORE (LS-SCORE)

We define a reference signal $r(n)$ by

$$r(n) = c^H X(n) \exp(j2\pi\alpha n), \quad (3.19)$$

where, the c is referred to the control vector ($c = [1 \ 0 \dots 0]^T$ is used in [17]), and $X(n)$ is defined in (3.1). The LS-SCORE cost function is defined by

$$F_{SC}(w, c) = \langle |y(n) - r(n)|^2 \rangle_T \quad (3.20)$$

Minimizing (3.20) with respect to w yields the LS-SCORE algorithm

$$w_{SC} = R_{xx}^{-1} r_{xr} \quad (3.21)$$

where $r_{xr} = \frac{1}{N} \sum_{k=1}^N X(k) r^H(k) \big|_{N \rightarrow \infty}$.

Cross-SCORE Algorithm

The motivation for developing the Cross-SCORE is that, in LS-SCORE algorithm, the control vector c is a constant vector. The vector c can be used to reject other signals and to speed convergence. The optimum weighting vector can be obtained from maximizing the strength of the cross-correlation coefficient between $y(n)$ and $r(n)$

$$F_{SC}(w, c) = \frac{|R_{yr}|}{R_{yy} R_{rr}} \quad (3.22)$$

$$= \frac{|w^H R_{xu} c|^2}{[w^H R_{xx} w] [c^H R_{uu} c]}$$

where $u(n)$ is defined to be the control signal.

$$u(n) = X(n) \exp(j2\pi\alpha n) \quad \text{and} \quad r(n) = c^H u(n) \quad (3.23)$$

After some derivation, it is found that w is optimized for fixed c by

$$w_{opt} \propto R_{xx}^{-1} R_{xu} c \quad (3.24)$$

Similarly, c is optimized for fixed w by

$$c_{opt} \propto R_{uu}^{-1} R_{ux} w \quad (3.25)$$

The optimum weighting vector w_{opt} is given by following eigenequation

$$\lambda R_{xx} w_{opt} = R_{xx} R_{uu}^{-1} R_{ux} w_{opt} \quad (3.26)$$

Auto-SCORE Algorithm

The auto-SCORE algorithm solves the problem of maximizing the spectral self-coherence strength at the output of a single linear combiner

$$F_{sc}(w) = |\rho_{yy}^\alpha| = \left| \frac{w^H R_{xx}^\alpha w}{w^H R_{xx} w} \right| \quad (3.27)$$

where $y(n) = w^H X(n)$. The cyclic autocorrelation matrix R_{xx}^α is in general non-Hermitian, hence, the auto-SCORE's objective function is in general equal to the magnitude of a complex ratio of quadratic forms (i.e., $|\rho_{yy}^\alpha|$ is not a generalized Rayleigh quotient) and can not be directly optimized

$$R_{xx}^{-1} R_{xx}^\alpha w = \lambda w \quad (3.28)$$

This solution can only be thought of as a suboptimal solution of the auto-SCORE algorithm and it is called Phase-SCORE in [20]. However, $|\rho_{yy}^\alpha|$ can be transformed to a true generalized Rayleigh quotient by replacing equation (3.27) with

$$\tilde{F}_{sc}(w) = |\tilde{\rho}_{yy}^\alpha| = \left| \frac{w^H \tilde{R}_{xx}^\alpha w}{w^H R_{xx} w} \right| \quad (3.29)$$

where $\tilde{R}_{xx}^\alpha$ is the Hermitianized cyclic autocorrelation matrix

$$\tilde{R}_{xx}^\alpha = \frac{1}{2} [R_{xx}^\alpha + R_{xx}^{\alpha H}] \quad (3.30)$$

Optimizing the objective function in (3.29) as suggested in [120] results in an optimum weight which is the eigenvector of the following eigenequation

$$R_{xx}^{-1} \tilde{R}_{xx}^\alpha w = \lambda w \quad (3.31)$$

associated with the largest eigenvalue.

In comparison later on, Auto-SCORE in (3.28) is used for its best performance among three SCORE algorithms [19].

3.5 CAB, C-CAB and R-CAB Algorithms [134,135,136]

Based on three different objective functions, the blind algorithms called CAB (Cyclic Adaptive Algorithm), C-CAB (Constrained CAB) and R-CAB (Robust CAB) are proposed

by exploiting the cyclostationarity of received signals.

CAB

The optimum weighting vector in CAB algorithm is determined by choosing w and an auxiliary weighting vector c so as to maximize the sample correlation between $w^H X(n)$ and $c^H u(n)$, that is $\max_w \max_c w^H R_{ux} c c^H R_{ux} w$ subject to $w^H w = 1$ and $c^H c = 1$ (3.32)

The solution of w can be easily shown by using the Lagrange multiplier method as

$$\lambda_{\max} w = \hat{R}_{ux} \hat{R}_{xu}^H w \quad (3.33)$$

The weighting vector w obtained from equation (3.33) is denoted by w_{CAB} .

C-CAB

It is easy to prove that CAB algorithm is an estimator of DOA of the desired user. In order to reject the co-channel interference, C-CAB algorithm is obtained by

$$\min_w w^H R_{xx} w \quad \text{subject to } w^H w = 1 \quad (3.34)$$

The optimum solution of equation (3.34) is given by

$$w_{C-CAB} = \hat{R}_{xx}^{-1} w_{CAB} \quad (3.35)$$

R-CAB

To achieve a more reliable beamformer scheme which is robust to various situations of interference, R-CAB is introduced by

$$\max_w \frac{|w^H A_o|^2}{w^H R_{nn} w} \quad \text{subject to } \frac{|w^H A_o|^2}{w^H w} = \delta \quad \text{and } w^H A_o = 1 \quad (3.36)$$

where R_{nn} is the covariance matrix of interference plus noise, and γ is a positive number.

The solution of this robust beamformer has been shown as

$$w \propto (R_{nn} + \gamma I)^{-1} d \quad (3.37)$$

where γ is the Lagrange multiplier for the first constraint of in equation (3.36).

3.6 Other Algorithms

Based on the idea of cyclostationary signal processing in [17,20,91], a new cost function for adaptive beamformer is proposed [95,96] by use of a particular class of non-

linear transformations.

The new cost function is defined as the error measurement between a complex sinusoid at frequency α and the p -th power of the array output.

$$J = \langle |e^{j2\pi\alpha n} - y^p(n)|^2 \rangle_N \quad (3.38)$$

where p is chosen according to the order of the periodicity exhibited by the desired signal. The selection of w to minimize this cost function can extract the complex-valued desired signal embedded in the array input, provided that the p -th power of desired signal contains a spectral line at frequency α .

It should be noted that cost function (3.38) differs from the CMA cost function (3.2) in that the $(\cdot)^p$ nonlinearity is used instead of the modulus nonlinearity $|\cdot|^p$. Unlike the SCORE algorithms which apply a cost function of the form of a Rayleigh quotient, the simplicity of this new cost function allows the derivation of a stochastic gradient algorithm to adaptively find the optimal weights. The instantaneous gradient of J can be easily computed as $-y^{p-1}(n)e^*(n)x(n)$, and the resulting stochastic gradient algorithm has the form,

$$w(n+1) = w(n) + \mu y(n) e^*(n) X(n) \quad (3.39)$$

where $e(n) = e^{j2\pi\alpha n} - y^p(n)$ and μ is the step size.

Like SCORE algorithm, this algorithm can capture the desired signal provided the signal of interest exhibits its cyclostationarity at α . The problem is that this algorithm converges very slowly. Simulation indicated that it will take about 5000 iterations to converge.

A flexible framework for blind adaptive spatial filtering is proposed by Schell and Gardner [50] in which CMA, Cross-SCORE can be considered as a special case of general blind algorithm.

3.7 Blind Equalization

So far, we have assumed that the channel model is flat fading. Although an antenna array has some equalization ability to reduce the ISI caused by frequency-selective fading, the algorithms reviewed only can pick up the signal which is a linear combination of

multipath signal for large time delay spread. In this case, a blind equalization technology is needed in order to reduce the ISI to the required level. In this thesis we concentrate on the blind signal estimation for the system with flat fading channel instead of blind channel estimation for frequency-selective channel. The blind identification and equalization algorithms are only briefly reviewed below.

A blind equalization scheme is shown in Figure 3.3. Instead of choosing the equalizer

Figure 3.3 A schematic blind equalization

so that the equalized output sequence $\{\hat{s}(n)\}$ is close to the source symbol sequence $\{s(n)\}$, as in standard equalization formulation, in blind equalization one chooses the equalizer so that the statistics of the equalized output $\{\hat{s}(n)\}$ are close to the statistics of the source symbol sequence $\{s(n)\}$. Blind equalization techniques are a special class of adaptive equalization algorithms where the identification and/or equalization of the unknown channel does not require an initial training sequence. Most current blind equalization algorithms use, directly or indirectly, high-order statistics of the received sequence in order to identify the unknown possibly nonminimum phase channel. (There exists a simple way to identify minimum phase channel [109]). Several blind channel

identification methods are proposed [110-115] based on the statistical properties of received data. A common characteristic of all these methods is slow convergence. This is because a larger number of samples must be processed before the estimates of the higher-order statistics become accurate. Recently [116,117], joint data and channel estimation based on the Maximum Likelihood (ML) criterion has been proposed to improve the convergence speed in blind equalization at the expense of computational complexity. In this method the channel is viewed as a finite-state encoder and a blind search of the underlying trellis is used to find the most probable transmitted sequence. The unknown channel is estimated in a decision-directed manner based on the MSE criterion. By exploiting the cyclostationarity of the received signal via oversampling, the blind identification and equalization algorithms are proposed in [97,98], to identify possibly nonminimum phase channels using only second-order statistics. This leads to more accurate estimation with a smaller sample size than methods using higher-order statistics. However, since the algorithms [97,98] work only in case of noise, they need to combine with other algorithms by which the cochannel can be rejected first, in order to apply this algorithm to real cellular communication environment. The algorithm proposed in this thesis can be used to fit this purpose.

3.7 Summary

The problems associated existing blind algorithms from the applications point of view are:

*** CMA

-- There is no guarantee that an array can capture the desired user if more than one user is involved in communication environment.

*** DOA finding method

-- In case of fading, the gain and phase information on each antenna element are random variables. In general, it is impossible to find the DOA of desired user through calculating the spatial spectrum, i.e., the algorithm will most likely fail.

*** SCORE and the blind algorithms based on cyclostationarity

-- Very slow convergence. It will take long time for the data sequence to demonstrate its cyclostationarity. It needs thousands or tens of thousands samples depending on the signal environments [120].

-- If more than one user exists in the communication system, the algorithm may fail to distinguish one from another, since algorithm is based on the cyclostationarity of the received signal data rate.

-- In Cross-SCORE and Auto-SCORE, the weighting vectors are obtained by optimizing some unconventional cost function. That is, optimizing these functions don't guarantee that the desired signal can be extracted in the sense of MMSE (minimum mean squared error) or MSINR (maximum signal to interference plus noise ratio).

-- In Cross-SCORE and Auto-SCORE, weighting vectors are obtained by solving the complex eigenequations.

-- Although it is proved that if the data collection time goes to infinity, the SCORE algorithm can provide the SENR close to DMI. In practice, it is more interesting to know the performance of algorithms based on finite data collection. That is, how the system performance related to the system parameters. Due to the complexity, SCORE algorithm hardly provides such analysis.

*** CAB, C-CAB and R-CAB

Since CAB family algorithms came to author's attention quite recently, and so no comparison study has been conducted. Some discussion are presented at the end of Chapter 7 in this thesis.

Chapter 4. Proposed Algorithms

This chapter describes two proposed algorithms: M-SCORE (Modified-SCORE) algorithm and PHASE algorithm and demonstrates their performances. Section 4.1 introduces the basic principle of antenna arrays, notations and signal model. The DMI algorithm is briefly reviewed for purposes of comparison later on. Section 4.2 and 4.3 present the M-SCORE and the comparison among DMI, SCORE and M-SCORE respectively. The PHASE algorithm is introduced in Section 4.4. The CTDMA (cyclic TDMA) in which each cochannel user has a slightly baseband frequency offset with others are introduced in Chapter 5. Comparison with conventional TDMA systems is made in terms of outage probability. The sensitivity of proposed algorithms to the perturbation of cyclostationarity is investigated in Section 4.5.

4.1 Introduction

Consider $N+1$ users in a radio communication environment, and an antenna array with M -elements at the base station. The spacing between elements is half a wavelength. Without loss of generality, let user number 1 be the desired user and the other N users be interferers. The signal vector received at the array at sample n is given by

$$\mathbf{X}(n) = [X_1(n) \ X_2(n) \ \dots \ X_M(n)]^T \quad (4.1)$$

where T is a transpose operation. The basic adaptive array structure is shown in Figure 4.1.

Suppose the desired signal (training sequence) is known at the receiver and represented by a reference signal $d(n)$. The difference between the desired array response and the actual array output signal defines an error signal

$$e(n) = d(n) - y(n) = d(n) - \mathbf{w}^H \mathbf{X}(n) \quad (4.2)$$

where H denotes complex conjugate transpose and $\mathbf{w}$ is a weighting vector. The magnitude squared error can therefore be written as

$$|e(n)|^2 = |d(n)|^2 - 2d(n) \mathbf{w}^H \mathbf{X}(n) + \mathbf{w}^H \mathbf{X}(n) \mathbf{X}^H(n) \mathbf{w} \quad (4.3)$$

Define the signal received at the input of antenna array as

Figure 4.1 Basic adaptive array structure with reference signal

$$\mathbf{X}(n) = \begin{bmatrix} X_1(n) \\ X_2(n) \\ \vdots \\ X_M(n) \end{bmatrix} = s_0(n) \mathbf{A}_0 + \sum_{i=1}^N s_i(n) \mathbf{A}_i + \mathbf{n}(n) \quad (4.4)$$

where

$$s_i(n) = d_i(n) \sin(2\pi f_i n) \quad (4.5a)$$

$$A_i = \left[\alpha_{1i} e^{j\theta_{1i}}, \alpha_{2i} e^{j\theta_{2i}}, \dots, \alpha_{Mi} e^{j\theta_{Mi}} \right]^T \quad i = 0, 1, \dots, N \quad (4.5b)$$

$$n(n) = \left[n_1(n) \ n_2(n) \ \dots \ n_M(n) \right]^T \quad (4.5c)$$

and $\alpha_{ij}(i=1,2,\dots,M; \text{ and } j=0,1,\dots,N)$ are the real i.i.d. random variables with Rayleigh distribution, $\theta_{ij}(i=1,2,\dots,M; \text{ and } j=0,1,\dots,N)$ are the random phase variables with uniform distribution over the range $[0, 2\pi]$, and $d_i(n)$ and $f_i (i=0,1,\dots,N)$ are the complex¹ data sequences and baseband carrier frequencies, explained below, respectively. Real-value $\{d_i(n)=\pm 1\}$ corresponds to BPSK, complex -value $\{d_i(n)\}$ to QPSK or QAM. The vectors $A_i(i=0,1,\dots,N)$ are called the directions of arrivals (DOAs) or the propagation vectors of the desired user and interfering users with the propagation loss and fading. In order to estimate DOAs, normally it is assumed that the DOAs $A_i(i=0,1,\dots,N)$ remain either unchanged or change very slowly during a frame period. Without losing generality, let $s_0(n)$ be the desired signal, $\{s_i(n)\} (i=1,2,\dots,N)$ be the independent interference signals, and $n(n)$ be a complex Gaussian noise vector.

Theoretically, the cyclostationarity of the signals in communication can be obtained from their bit rate or symbol rate. Unfortunately, this not only limits the application to an environment where each user transmits a slightly different bit rate, but also take a long time for the system to distinguish one user from another on the basis of different symbol rate[84]. Therefore, it is not useful in the situation where antenna weights have to be adapted over a short period of time in order to track the changes in the channels. In algorithms considered in this thesis, the cyclostationarity of the data is achieved by assigning each user a unique baseband carrier frequency (BCF) $f_i (i=0,1,\dots,N)$ where in general the frequency offset between the neighboring users is much less than the signal bandwidth[18]. The idea is demonstrated in Figure 4.2. In a TDMA system, cochannel users share the same bandwidth. For the proposed CTDMA system, the desired user has

1. Subsequently we will specify the $\{d_i\}$ to the BPSK case, i.e., $d_i = \pm 1$

some frequency offset with cochannel users. In this case, algorithms converge much faster than ones which use the signal bit rate or baud rate cyclostationarity, which makes the algorithms useful in mobile communication.

There are two options to achieve the cyclostationarity by assigning the baseband carrier frequency to each user. Equation (4.5a) shows the first possibility. Another option is to choose $s_i(n) = d_i(n) e^{-j2\pi f_i n}$ instead of $s_i(n) = d_i(n) \sin(2\pi f_i n)$ as the transmitted signal. From the SINR and demodulation point of views, the latter signal modulation will provide a more practical solution to extract the desired signal in a communication environment. In the next few sections, the algorithms are derived based on the signal model in (4.5a). The results for a second signal model are given in Appendix D. The comparison between them will be made in Section 4.4.3.

4.1.1 Direct Matrix Inversion [24]

The asymptotic sample covariance of $X(t)$ is given by

$$R_{xx} = \frac{1}{N} \sum_{k=1}^N X(k) X^H(k) \big|_{N \rightarrow \infty} = P_0 A_0 A_0^H + \sum_{l=1}^L P_l A_l A_l^H + \sigma^2 I \quad (4.6)$$

and the correlation between the $X(n)$ and the reference is given by

$$r_{xr} = \frac{1}{N} \sum_{k=1}^N X(k) r^H(n) \big|_{N \rightarrow \infty} = P_0 A_0 \quad (4.7)$$

where $P_l = E[|s_l(n)|^2]$ and $\sigma^2 = E[|n_l(n)|^2]$ are the signal powers of the l -th user and noise respectively. N is the number of samples used for calculation. It follows that the optimum choice or the MSE solution for the weighting vector must satisfy

$$R_{xx} w_{opt} = r_{xr}; \quad \text{or} \quad w_{opt} = R_{xx}^{-1} r_{xr} \quad (4.8)$$

so that

$$w_{MSE} = w_{opt} = P_0 R_{xx}^{-1} A_0 \quad (4.9)$$

which meets $\min \sum_{k=1}^N |w_{MSE}^H X(k) - r(k)|^2 \big|_{N \rightarrow \infty} = E[|r(k)|^2] - r_{xr}^H R_{xx}^{-1} r_{xr}$. Comparing

(4.7) with A_0 , it is clear that r_{xr} is the DOA of the desired user except for the scale factor [24] and can be expressed as

-- Frequency assignment to cochannel users

Figure 4.2. The channel assignment schemes of TDMA and CTDMA

$$P_0 \mathbf{A}_0 = E(s_0(n)^2) [\alpha_{10} e^{j\theta_{11}} \quad \alpha_{20} e^{j\theta_{21}} \quad \dots \quad \alpha_{M0} e^{j\theta_{M1}}]^T \quad (4.10)$$

It is shown in [121] that $\mathbf{R}^{-1}_{xx}$ is a projector which makes the optimum weight vector $\mathbf{w}_{MSE}$ emphasize the desired signal, and puts nulls on the DOAs of the interferences. The performance of the optimum weight can be seen clearly in following example. Assume that there is only one user and one interference with the directional arrival vector $\mathbf{A}_0$ and $\mathbf{A}_1$ respectively. Using the matrix inverse identity (details are presented in Appendix B), we have

$$\mathbf{w}_{MSE} = \frac{1}{\sigma^2 (1 + P_0 \mathbf{A}_0^H \mathbf{R}_{nn}^{-1} \mathbf{A}_0)} \left(\mathbf{A}_0 - \frac{MP_1 d}{MP_1 + \sigma^2} \mathbf{A}_1 \right) \quad (4.11)$$

where $\mathbf{A}_i^H \mathbf{A}_i = M$ and $d = \mathbf{A}_0^H \mathbf{A}_1 / M = \mathbf{A}_1^H \mathbf{A}_0 / M$. d can be considered as the correlation coefficient (CC) between $\mathbf{A}_0$ and $\mathbf{A}_1$, and ranges over $[-1, 1]$. $\mathbf{R}_{nn}$ is an interference plus noise matrix. It is easy to see that, if $MP_1 \gg \sigma^2$, then

$$\begin{aligned} \mathbf{w}_{MSE}^H \mathbf{A}_0 &= \frac{1}{\sigma^2 (1 + P_0 \mathbf{A}_0^H \mathbf{R}_{nn}^{-1} \mathbf{A}_0)} (M - Md^2) \\ \mathbf{w}_{MSE}^H \mathbf{A}_1 &= \frac{1}{\sigma^2 (1 + P_0 \mathbf{A}_0^H \mathbf{R}_{nn}^{-1} \mathbf{A}_0)} (Md - Md) = 0; \end{aligned} \quad (4.12)$$

i.e. $\mathbf{w}_{MSE}$ is orthogonal to $\mathbf{A}_1$ and the antenna array nulls the interference completely. However, the performance will degrade with increase of d and noise level. If $d=1$, which means that both DOAs of the user and interference overlap, the array cannot do anything against the interference. If $MP_1 \gg \sigma^2$ does not hold, the array can not completely reject the interference. In this case the null depth is dependent on the ratio of MP_1 to σ^2 .

It should be noted that the result in (4.9) is obtained under the assumption that both the covariance matrix $\mathbf{R}_{xx}$ and the directional arrival vector $\mathbf{A}_0$ of the user can be found exactly when the data collection time N approaches infinity. In application, the usefulness

of an adaptive array critically depends on the convergence rate that can be achieved. The result in (4.9), in practice, will be modified as

$$\hat{w}_{opt} = \hat{R}_{xx}^{-1} \hat{A}_0 \quad (4.13)$$

regardless of the constant P_0 , where, $\hat{R}_{xx}$ is the N sample covariance estimate of R_{xx} , $\hat{A}_0$ is the sample cross-correlation vector estimation of A_0 , that is

$$\hat{R}_{xx} = \frac{1}{N} \sum_{k=1}^N X^H(k) X(k) \quad \text{and} \quad \hat{A}_0 = \frac{1}{N} \sum_{k=1}^N X(k)^H r(k) \quad (4.14)$$

It is proved in [122] that both $\hat{R}_{xx}$ and $\hat{A}_0$ are the maximum likelihood estimations of R_{xx} and A_0 . The Algorithm in (4.13) is called Direct Matrix Inversion(DMI) algorithm [119]. In application, DMI can be efficiently implemented with the RLS algorithm as shown in Section 4.4.3.

4.2 M-SCORE Algorithm

On the other hand, using the result in (3.17), the objective function of Auto-SCORE algorithm in (3.27) can be rewritten as

$$F_{sc}(w) = \left| \rho_{yy}^\alpha \right| = \left| \frac{w^H R_{00}^\alpha A_0 A_0^H w}{w^H R_{xx} w} \right| \quad (4.15)$$

It is proved in [123] that the optimum weight for equation (4.15) is given by

$$w_{opt} = \mu R_{xx}^{-1} A_0, \quad (4.16)$$

where, μ is a constant which makes $|w_{opt}| = 1$. Comparing equation (4.16) with equation (4.9), it is seen that if the data collection time N approaches infinity, both the optimum weight vectors are of the same forms except the scale factor and, of course, also give the same output SINR performances.

As shown in (4.15) and (4.16), if the data collection time goes to infinity, the Auto-SCORE has the same weight vector as DMI does. However a problem arises when the data collection time N is finite, then R_{ii}^α and R_{nn}^α are not equal to zero and equation (3.17) does not hold. The results in (4.15) and (4.16) suggest another way to solve this problem: that is,

estimate the A_0 using the eigen-decomposition method, even if the data collection time N is finite.

For the finite time data collection, the matrix in (3.17) can also be expressed in terms of its eigenvectors as

$$\hat{R}_{xx}^{\alpha} = U \Sigma V^H = \sum_{k=1}^M \lambda_k u_k v_k^H \quad (4.17)$$

where, $U=[u_1 \ u_2 \dots \ u_M]$ and $V=[v_1 \ v_2 \dots \ v_M]$ are the right and left eigenvectors associated with the eigenvalues $\lambda_k(k=1,2,\dots,M)$ of $\hat{R}_{xx}^{\alpha}$ (assuming that $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_M$) and Σ is a diagonal matrix. The proposed algorithm called M-SCORE algorithm will calculate the optimum weight according to following procedures: First solve the eigenequation

$$\hat{R}_{xx}^{\alpha} w = \lambda w \quad (4.18)$$

and then choose the vector

$$\hat{w}_{M-SCORE} = \hat{R}_{xx}^{-1} w_1 \quad (4.19)$$

as the estimate optimum weight vector, where w_1 is the right eigenvector associated with the largest eigenvalue in equation (4.18). It will be proved in next section that, under certain conditions, the eigenvector w_1 is a good estimation of A_0 .

4.3 Comparison of DMI, Auto-SCORE, and M-SCORE

In the following section, the output SINRs of DMI in (4.9), Auto-SCORE in (3.28), and M-SCORE in (4.18) are compared if the data collection time goes to infinity and there is one interferer. For the finite data collection, the explicit formulas of optimum weights for M-SCORE are also derived. Since it is too complicated to give the explicit formula for Auto-SCORE in terms of system parameters; only the performances of M-SCORE and DMI are compared in this chapter. But the performance of Auto-SCORE are compared with M-SCORE and DMI in simulation presented in Chapter 5 under the condition of finite data collection.

4.3.1 Infinite data collection time

Suppose there is only one user and one interference, and the data collection time goes to infinity. The covariance and cyclic correlation matrix in equation (3.4) and (3.17) can be

rewritten as

$$R_{xx} = P_0 A_0 A_0^H + P_1 A_1 A_1^H + \sigma^2 I \quad (4.20)$$

$$R_{xx}^\alpha = R_{00}^\alpha A_0 A_0^H$$

Similar to P_0 , P_1 , and σ^2 are the desired signal, interference and noise powers respectively.

Equivalently, R_{00}^α , R_{11}^α and R_{nn}^α can also be considered as the desired signal, interference and noise powers respectively after cyclic correlation operation. We define

$$SNR = \frac{P_0}{\sigma^2}, INR = \frac{P_1}{\sigma^2}, S^\alpha NR = \frac{R_{00}^\alpha}{\sigma^2}, I^\alpha NR = \frac{R_{11}^\alpha}{\sigma^2}, \text{ and } N^\alpha NR = \frac{R_{nn}^\alpha}{\sigma^2} \quad (4.21)$$

For Auto-SCORE algorithm, using the results in Appendix B, the eigenequation (3.28) becomes

$$R_{xx}^{-1} R_{xx}^\alpha w = \left(\frac{(1 + M \times INR) SNR \alpha}{k} A_0 A_0^H - \frac{Md \times INR \times SNR \alpha}{k} A_1 A_0^H \right) w = \lambda w \quad (4.22)$$

where

$$k = \frac{1}{1 + M \times SNR} \left(1 + P_1 A_1^H R_{xx}^{-1} A_1 \right) = \frac{1}{1 + M \times SNR} \left(1 + \frac{P_1}{\sigma^2} \left(M - \frac{M^2 d^2 P_0}{\sigma^2 + M P_0} \right) \right)$$

(details are given in appendix B).

It is proved in [125] that the eigenvector corresponding to the largest eigenvalue is a linear combination of A_0 and A_1 . Using the results in Appendix A for the case $k_3=0$ and $k_4=0$, the eigenvector of equation (4.22) corresponding to the largest eigenvalue is of the form

$$w_{SCORE} = c_1 (A_0 - d A_1) \quad (4.23)$$

where, c_1 is a constant and will not affect the output SINR of antenna array, and $d = A_0^H A_1 / M = A_1^H A_0 / M$. Using the results in equation (4.11), the optimum weight for M-SCORE is also of the form

$$w_{M-Score} = R_{xx}^{-1} A_0 = c_2 (A_0 - dA_1) \quad (4.24)$$

where, in (4.23) and (4.24), it is assumed that $MP_i \gg \sigma^2$ and c_2 is another constant. Both Auto and M-SCORE algorithms can extract the signal exactly and give the same output SINR performance as DMI does when the data collection time goes to infinity.

4.3.2 Finite data collection time

If the data collection time is finite, in general, $\hat{R}_{11}^\alpha \neq 0$ and $\hat{R}_{nn}^\alpha \neq 0$. The cyclic correlation matrix at frequency shift at α is given by (3.18). (The specific formula of $\hat{R}_{00}^\alpha$, $\hat{R}_{11}^\alpha$ for BPSK are shown in Appendix D). Following the same procedures in section 4.3.1, for the Auto-SCORE algorithm, we have

$$\begin{aligned} \hat{R}_{xx}^{-1} \hat{R}_{xx}^\alpha w = & \frac{(1 + M \times INR) \left(S^\alpha NR - N^\alpha NR \times SNR \right)}{k} A_0 A_0^H + \\ & \frac{MdSNR \left(N^\alpha NR \times INR - I^\alpha NR \right)}{k} A_0 A_1^H + \frac{MdINR \left(N^\alpha NR \times SNR - S^\alpha NR \right)}{k} A_1 A_0^H \quad (4.25) \\ & + \frac{(1 + MSNR) \left(I^\alpha NR - N^\alpha NR \times SNR \right)}{k} A_1 A_1^H + \left(N^\alpha NR \right) I = \lambda w \end{aligned}$$

The eigenvector of equation (4.25) is of the form

$$\hat{w}_{SCORE} = \mu_1 (A_0 + y_1 A_1) \quad (4.26)$$

where, μ_1 is a constant for given M , SNR , INR , $S^\alpha NR$, $I^\alpha NR$, $N^\alpha NR$, and d ; and will not affect the output SINR. y_1 is the solution of following quadratic equation as shown in Appendix A:

$$c_1 y^2 + c_2 y + c_3 = 0; \quad (4.27)$$

where, c_1 , c_2 , and c_3 are also the functions of M , SRN , IRN , SRN^α , IRN^α , NNR^α , and d . Unfortunately, y_1 is a complicated function of system parameters.

For M-SCORE algorithm, the eigenvector of matrix in equation (4.18) is also of the form

$$w = \mu_2 (A_0 + y_2 A_1) \quad (4.28)$$

and the optimum weight is given by

$$\hat{w}_{M-SCORE} = \mu_2 \hat{R}_{xx}^{-1} (A_0 + y_2 A_1) \quad (4.29)$$

where, μ_2 is a constant and y_2 is the solution of a quadratic equation (4.27) but have different parameters c_1 , c_2 , and c_3 from that in Auto-SCORE algorithm.

Since, in practice, $R_{00}^\alpha \gg |R_{11}^\alpha|$ if $N > 3/\Delta\alpha$ (proven in Appendix E) and $d < 1$, using the result (presented in Appendix A), y in equation (4.28) it can be found that, after cyclic-correlation operation,

$$y_2 \approx \frac{R_{11}^\alpha}{R_{00}^\alpha} d \quad (4.30)$$

For instance, in BPSK, suppose

$$|R_{00}^\alpha| = 0.25 \quad \text{and} \quad |R_{11}^\alpha| = 0.025 \quad (4.31)$$

The results for y_2 in (4.28) calculated from equation (4.27) are shown in Table 1.

Table 4.1 y_2 with the change of d

d	y_2	d	y_2
0.1	-0.0091	0.6	-0.0563
0.2	-0.0182	0.7	-0.0664
0.3	-0.0275	0.8	-0.0770
0.4	-0.0369	0.9	-0.0882
0.5	-0.0464	1.0	-0.1000

It is shown in Table 4.1 that the y_2 value is quite small and that (4.28) is a reasonably good approximation.

Comparing with equations (4.13), it is seen that, without concerning the constant, the weight vector in M-SCORE has the form

$$\hat{w}_{M-SCORE} = \hat{R}_{xx}^{-1} (A_0 + y_2 A_1) = \hat{w}_{DMI} + y_2 \hat{R}_{xx}^{-1} A_1 = \hat{w}_{DMI} + \Delta w_1 \quad (4.32)$$

when the data collection time is finite. Since y_2 is normally small, it is expected that (4.28) gives a good estimation of A_0 . The component Δw_1 is contributed by the interference. In Auto-SCORE, the weight vector can also be rewritten as

$$\begin{aligned}\hat{w}_{Auto-SCORE} &= A_0 + y_1 A_1 = \\ A_0 - \frac{MP_1 d}{MP_1 + \sigma^2} A_1 + \left(y_1 + \frac{MP_1 d}{MP_1 + \sigma^2} \right) A_1 &= w_{MSE} + \Delta w_2\end{aligned}\quad (4.33)$$

In this sense, both weight vectors in Auto-SCORE and M-SCORE can be considered as the estimation of $\hat{w}_{DMI}$ and w_{MSE} with errors Δw_1 and Δw_2 respectively. However, it is hard to find the expression of y_1 due to the complexity of equation (4.25).

The advantage of the explicit specific formula of optimum weight vector of M-SCORE algorithm in (4.29) is that we can improve the performance by using the results of the finite data collection in [124]. It is shown in Appendix C, the covariance matrix over finite data samples can be expressed as

$$\hat{R}_{xx} = \hat{V}_s \hat{\Sigma}_s \hat{V}_s^H + \hat{V}_n \hat{\Sigma}_n \hat{V}_n^H \quad (4.34)$$

where definitions of the terms in (4.34) are given in Section 3.3. As suggested in [124], the optimum weight vector in (3.39) can be rewritten as

$$\hat{w}_{M-SCORE} = \hat{V}_s \hat{\Sigma}_s^{-1} \hat{V}_s^H (A_0 + y_2 A_1) \quad (4.35)$$

We call the algorithm given by (4.29) the M-SCORE-I algorithm, the algorithm given by (4.35) as M-SCORE-II algorithm.

Another advantage is that the SINR of the array can also be expressed in terms of system parameters as shown below. If the output SINR of the array is defined as

$$SINR(w) = \frac{w^H P_0 A_0 A_0^H w}{w^H P_1 A_1 A_1^H w + \sigma^2 w^H w} \quad (4.36)$$

for the case of one desired user and one interferer and let $MP_1(1-d^2) \gg \sigma^2$, then after some manipulation, we have, using the results in Appendix b

$$\frac{SINR(w_{I-SCORE})}{SINR(w_{DMI})} = 1 - M \left(1 - d^2 \right) d^2 I^{\alpha} I R \times I^{\alpha} N R \quad (4.37)$$

It is seen from (4.37) how the performance of M-SCORE algorithm is related to the number of elements in the array M , the ratio of the power of interfering signal after and

before cyclic-correlation operation, the ratio of the power of interfering signal after cyclic-correlation to the noise, the correlation coefficient d between the user and interference propagation vectors and the input SNR.

In chapter 5, the simulations are used to evaluate the performances of Auto-SCORE and M-SCORE by comparing with the DMI algorithm.

4.4 PHASE Algorithm

4.4.1 The Derivation of the PHASE Algorithm

There are three motivations for us to propose the PHASE algorithm. First, it is clear in (3.20) that the performance of the SCORE algorithm is dependent on the convergence rate of the cyclic-autocorrelation operation. Based on the finite data collection, it is expected that a desired algorithm will converge fast enough so that the system can be adapted quickly enough to track the changes of the communication environment. The more the cyclic-autocorrelation of interference and noise can be reduced, the more accuracy of DOA estimation can be obtained. Second, In SCORE and M-SCORE algorithms, we have to solve the eigenequation in order to find the optimum weight vector. Since the eigenvalue of the eigenequation approaches zero due to the cyclic correlation operation, it is not an easy to estimate the eigenvector accurately[89]. Although it is possible to avoid eigenvector computations for LS-SCORE and the power method Cross-SCORE [17], the former method suffers from slow convergence while the latter requires the adaptation of two beamformers simultaneously. Third, the optimum weighting vector is defined as the eigenvector corresponding to the largest eigenvalue. Simulations show that, in the presence of interference, there may be two very close eigenvalues in Auto-SCORE. Due to the ill-behaved matrix, it is possible that the algorithm may pick up the wrong eigenvector as the optimum weighting vector. In this case, the algorithm will fail to extract the desired signal, which degrades the system performance considerably. Therefore, we try to seek a simpler and effective and less computationally intensive algorithm and to get more accurate estimation of DOA.

In the following, based on the cyclostationarity of the signals, the algorithms called PHASE are derived to estimate the DOA of desired user. The structure of PHASE

algorithm for $M=2$ is shown in Figure 4.3. Let us start from the situation that the first antenna output is chosen as the reference. The objective function of the PHASE algorithm is defined as

$$F(w_1) = \langle |y(n) - r_1(n)|^2 \rangle_N \quad (4.38)$$

where, $y(n) = w_1^H X(n)$, and $r_1(n)$ is given by

$$r_1(n) = X_1(n) e^{-j2\pi f_1 n} \quad (4.39)$$

f_1 is the baseband carrier frequency which is assigned uniquely to the desired user and $\langle \cdot \rangle_N$ denotes time-averaging over the interval $[0, N]$. Since it is shown in [20] that if $r_1(n)$ and $X(n)$ are spectrally self-coherent at the frequency separation at $\alpha = 2f_1$ and equation (4.38) is of the standard form of least square algorithm, so the optimum weight vector is given by

$$R_{xx} w_1 = R_1^\alpha \quad \text{or} \quad w_1 = R_{xx}^{-1} R_1^\alpha \quad (4.40)$$

where

$$R_1^\alpha = \langle X(n) r_1^*(n) \rangle_N \quad (4.41)$$

The mean value of R_1^α is

$$E\left(s_0(n)^2\right) \left[|\alpha_{10}|^2 \quad \alpha_{20} \alpha_{10}^* e^{j\theta_{20} - \theta_{10}} \quad \dots \quad \alpha_{M0} \alpha_{10}^* e^{j\theta_{M0} - \theta_{10}} \right]^T \quad (4.42)$$

where, α_{ij} is the same as defined in (3.5). It is noted that the weighting vector in (4.40) is also the solution of LS-SCORE in [17]. Comparing (4.42) with (4.10), we find that both solutions have the same form and can be used to combine the signals received at each antenna elements. The difference is that in (4.10) the DOA of desired user is estimated directly and in (4.42), only the relative phase difference between the antenna elements are estimated. The details of derivation of (4.42) is given in Appendix D for reference

If the reference signal is chosen as

$$r_i(n) = X_i(n) e^{-j2\pi f_i n} \quad (4.43)$$

$i = 2, 3, \dots, M$ respectively, we have

needed.

Auto-SCORE algorithm:

The optimum weighting vector of Auto-SCORE algorithm is given by following equation

$$\hat{R}_{xx}^{-1}(k) \hat{R}_{xx}^{\alpha}(k) \hat{w}(k) = \lambda \hat{w}(k) \quad (4.66)$$

where $\hat{w}(k)$ is the eigenvector corresponding to the largest eigenvalue in (4.47) and

$$\hat{R}_{xx}^{\alpha}(k) = \sum_{i=1}^k X(k) X^H(k) e^{j2\pi\alpha i} \quad (4.67)$$

$M^*(M+1)/2$ complex multiplications are required to form (4.67), M^2 complex multiplications to calculate $\hat{R}_{xx}^{-1}(k) \hat{R}_{xx}^{\alpha}(k)$ and $1.75M^2 + 2.25*M$ multiplications for $P(k)$. Additionally, the power method [133] is needed to find the eigenvector of equation (4.66). In this case, at least M^2 complex multiplications are needed for each iteration by using power method. Total complex multiplications for Auto-SCORE algorithm is $(3.25+n)M^2 + 2.75M$, where n is the number of iterations needed to solve equation (4.66) with power method which depends on the distribution of eigenvalues of (4.66).

4.4.4 Two-mode algorithm

In application, it is possible to combine the DMI with the PHASE algorithm to achieve better output SINR than by using PHASE alone. For instance, at the beginning of adaptation, PHASE is used to start up blindly. After some point, say $n_0=40$, when the output SINR is reasonably high and the BER (bit error rate) is less than 10^{-3} , DMI takes over, using the estimated data symbols as a reference to adapt the weighing coefficient sample by sample.

Let's assume that at n_0 , PHASE algorithm is shifted to DMI. Ideally, the following equation can be used for update the optimum weighting vector.

$$\hat{w}_T(n_0 + 1) = \hat{w}_P(n_0) + \Delta \hat{w}_{DMI}(n_0) \quad (4.68)$$

where subscript T denotes the two-mode algorithm, $\hat{w}_P(n_0)$ is optimum weighting vector

$$\begin{aligned}
 R_2^{2f_1} &= \langle X(n) r_2^*(n) \rangle_N = \begin{bmatrix} R_{12}^{2f_1} & R_{22}^{2f_1} & \dots & R_{M2}^{2f_1} \end{bmatrix}^T \\
 &= \begin{bmatrix} P_{12} e^{j(\theta_{11} - \theta_{21})} & P_{22} & \dots & P_{M2} e^{j(\theta_{M1} - \theta_{21})} \end{bmatrix}^T \\
 &= e^{j(\theta_{11} - \theta_{21})} \begin{bmatrix} P_{12} & P_{22} e^{j(\theta_{21} - \theta_{11})} & \dots & P_{M2} e^{j(\theta_{M1} - \theta_{11})} \end{bmatrix}^T \\
 &\quad \dots \dots \dots
 \end{aligned}
 \tag{4.44}$$

$$\begin{aligned}
 R_M^{2f_1} &= \langle X(n) r_M^*(n) \rangle_N = \begin{bmatrix} R_{1M}^{2f_1} & R_{2M}^{2f_1} & \dots & R_{MM}^{2f_1} \end{bmatrix}^T \\
 &= \begin{bmatrix} P_{1M} e^{j(\theta_{11} - \theta_{M1})} & P_{2M} e^{j(\theta_{21} - \theta_{M1})} & \dots & P_{MM} \end{bmatrix}^T \\
 &= e^{j(\theta_{11} - \theta_{M1})} \begin{bmatrix} P_{1M} & P_{2M} e^{j(\theta_{21} - \theta_{11})} & \dots & P_{MM} e^{j(\theta_{M1} - \theta_{11})} \end{bmatrix}^T
 \end{aligned}
 \tag{4.45}$$

where,

$$P_{ij} = P_1 \langle \alpha_{i1} \alpha_{j1}^* \rangle_N \quad \begin{matrix} i = 1, 2, \dots, M \\ j = 1, 2, \dots, M \end{matrix} \quad P_1 = \langle s_1(n) s_1^*(n) \rangle_N \tag{4.46}$$

the optimum weight vectors by choosing the different signals as the reference are given by

$$\mathbf{w}_i = \mathbf{R}_{xx}^{-1} \mathbf{R}_i^{2f_1} \quad i = 2, 3, \dots, M \tag{4.47}$$

It is known that, in case of the fading, any one of M antennas in the array may suffer from deep fading over the period of adaptation. The weight vector will not provide good performance if the channel in deep fade is chosen as reference. Therefore, it is quite reasonable to combine the weighting vectors in (4.42) and (4.44). On the other hand, although as shown in (4.42) and (4.44) the cyclic-correlation can completely cancel the interference and noise, in practice, due to the finite data collection, those terms will not be zero. Since the interference and noise terms can be considered as an equivalent complex Gaussian noise, the noise will be reduced and the accuracy of estimation will be improved

by combining the weighting vectors. This is validated by the simulation results in the next chapter.

There exist two linear combining methods in which these M optimum weighting vector can be cophased. The combining vector in maximum ratio combining (MRC) sense is

$$w_{mrc} = R_{xx}^{-1} \sum_{i=1}^M \gamma_i R_i^{\alpha} \quad (4.48)$$

where

$$\gamma_i = \frac{R_{i1}^{\alpha*}}{\sum_{l=1}^M |R_{il}^{\alpha}|^2} \quad (4.49)$$

and R_{i1}^{α} is the first element of vector R_i^{α} .

The combining vector in equal gain combining (EGC) sense is

$$w_{egc} = R_{xx}^{-1} \sum_{i=1}^M \gamma_i R_i^{\alpha} \quad (4.50)$$

where

$$\gamma_i = \frac{R_{i1}^{\alpha*}}{|R_{i1}^{\alpha}|} \quad (4.51)$$

Actually, PHASE algorithm is a special case of LS-SCORE or cross-SCORE. The main difference is how to choose the control vector c in (3.19). In LS-SCORE algorithm, the control vector c is constant and equal to $[1 \ 0 \ \dots \ 0]$ in [17]. In cross-SCORE, the control vector c is adapted by the eigenequation in order to reject the interferences. In PHASE, the control vector c is chosen as

$$c = [\gamma_1 \ \gamma_2 \ \dots \ \gamma_M] \quad (4.52)$$

to make the combining weighting vector not only extract the desired signal, and also reject the interference. Here γ_i $\{i=1,2,\dots,M\}$ are given in (4.49) or (4.51). The simulations show

that the MRC will provide the better performance than EGC in case of fading as shown in Table 5.2 in Chapter 5.

4.4.2 Comments on PHASE Algorithm

In previous sections, we did not mention any specific modulation signal used. All the algorithms presented before can be applied to the signal

$$s(n) = d(n) \sin(2\pi f n) \quad n = 1, 2, \dots \quad (4.53)$$

where, f is baseband carrier frequency, $s(n)$ is a complex data sequence. There are two problems that need to be investigated before they can be used in practice. First, as mentioned that, f is the baseband frequency by which we can distinguish the desired user from the interference through the cyclic-correlation operation. It is noted that $u(n)$ in (4.53) is easily susceptible to interference and noise since $\sin(2\pi f_1 n)$ becomes small periodically (when $2\pi f_1 n$ is close to $\pm k\pi$). This phenomenon certainly will degrade the SINR of the antenna array and increase the bit error probability(BEP). Second, it is very difficult, if not impossible, to remove the baseband carrier at the output of array by using any kind of demodulation technique that is used for the conventional high carrier frequencies.

In order to avoid these two problems, we can also use

$$s(n) = d(n) e^{-j2\pi f n} \quad n = 1, 2, \dots \quad (4.54)$$

as the transmitted signal instead of (4.53). In this case, the $\exp(-j2\pi f n)$ does not change the magnitude of $s(n)$ anytime and is also easily demodulated to the baseband frequency at the receiver. In order to use the signal model in (4.54), some modifications are needed. Instead of using (4.41) to calculate R_i^α , we change to

$$R_i^\alpha = \langle X(n) r_i(n) \rangle_N \quad (4.55)$$

This preserves the phase information and cancels the baseband carrier frequency. In this case, the $s(n)$ in (4.54) must be a real data sequence. The derivation of the optimum weighting vector by using the modulation signal in (4.54) is given in Appendix D. Since our subsequent investigations show that the performance of algorithm using (4.54) converges much faster than using (4.53), all simulation results presented in rest of thesis are based on signal model given by (4.54), i.e. a frequency-shifted BPSK signal.

4.4.3 Recursive Implementation and the Complexities of DMI, PHASE and Auto-SCORE Algorithms

For finite data collection, DMI, PHASE and Auto-SCORE algorithms can be rewritten in recursive forms:

DMI algorithm:

The optimum weighting vector of DMI algorithm is given by

$$\hat{w}_{DMI}(k) = \hat{R}_{xx}^{-1}(k) \hat{r}_{xd}(k) \quad (4.56)$$

where

$$\begin{aligned} \hat{R}_{xx}(k) &= \frac{1}{k} \sum_{i=1}^k X(i) X^H(i) \\ &= \hat{R}_{xx}(k-1) + X(k) X^H(k) \end{aligned} \quad (4.57)$$

and

$$\begin{aligned} \hat{r}_{xd}(k) &= \sum_{i=1}^k X(i) d(i) \\ &= \hat{r}_{xd}(k-1) + X(k) d(k); \quad \hat{r}_{xd}(k) = 0 \end{aligned} \quad (4.58)$$

$\{d(k)\}$ is a training sequence.

Define

$$P(k) = \hat{R}_{xx}^{-1}(k) \quad (4.59)$$

then, if $P(0)$ is initialized as $\frac{1}{\delta} I$, where δ is a small constant, (4.56) and (4.59) can be updated using the RLS algorithm

$$P(k+1) = P(k) - \frac{P(k) X(k+1) X^H(k+1) P(k)}{1 + X^H(k+1) P(k) X(k+1)} \quad (4.60)$$

and

$$\hat{w}_{DMI}(k+1) = \hat{w}_{DMI}(k) + \frac{P(k)X(k+1) \left(d(k+1) - X^H(k+1) \hat{w}_{DMI}(k) \right)^*}{1 + X^H(k+1)P(k)X(k+1)} \quad (4.61)$$

From [24], the updating computation represented by (4.60) requires M^2 complex multiplications to form $P(k)X(k+1)$. Furthermore (4.60) requires an additional $0.75M^2 + 2.25M$ complex multiplications. To form (4.61), $2M$ complex multiplications are needed. The total computation needed is $1.75M^2 + 5.25M$ complex multiplications.

PHASE Algorithm:

The optimum weighting vector of PHASE algorithm is give by

$$\hat{w}_P(k) = \sum_{i=1}^M \hat{\gamma}_i(k) \hat{w}_{P_i}(k) \quad (4.62)$$

where

$$\hat{w}_{P_i}(k) = \hat{R}_{xx}^{-1}(k) \hat{R}_i^\alpha(k) \quad (4.63a)$$

$$\hat{R}_i^\alpha(k) = \sum_{j=1}^k X(j) r_i(j) = \hat{R}_i^\alpha(k-1) + X(k) r_i(k) \quad (4.63b)$$

$$r_i(k) = X_i(k) e^{j2\pi\alpha k} \quad (4.63c)$$

and same as difined in (4.49)

$$\hat{\gamma}_i(k) = \frac{\hat{R}_{i1}^\alpha(k)}{\left| \hat{R}_{i1}^\alpha(k) \right|^2} \quad i = 1, 2, \dots, M \quad (4.64)$$

In recursive form, we have

$$\hat{w}_{P_i}(k+1) = \hat{w}_{P_i}(k) + \frac{P(k)X(k+1) \left(r_i(k+1) - X^H(k+1) \hat{w}_{P_i}(k) \right)^*}{1 + X^H(k+1)P(k)X(k+1)} \quad (4.65)$$

$P(k)$ is updated as in (4.60).

In addition to calculate $P(k)$, $2M^2$ complex multiplications are required to form M weighting vector in (4.65). M multiplications for (4.63b), $2M$ multiplications for (4.64), and M multiplications for (4.62). Totally, $3.75M^2 + 6.25M$ complex multiplications are

needed.

Auto-SCORE algorithm:

The optimum weighting vector of Auto-SCORE algorithm is given by following equation

$$\hat{R}_{xx}^{-1}(k) \hat{R}_{xx}^{\alpha}(k) \hat{w}(k) = \lambda \hat{w}(k) \quad (4.66)$$

where $\hat{w}(k)$ is the eigenvector corresponding to the largest eigenvalue in (4.47) and

$$\hat{R}_{xx}^{\alpha}(k) = \sum_{i=1}^k X(k) X^H(k) e^{j2\pi\alpha i} \quad (4.67)$$

$M^*(M+1)/2$ complex multiplications are required to form (4.67), M^2 complex multiplications to calculate $\hat{R}_{xx}^{-1}(k) \hat{R}_{xx}^{\alpha}(k)$ and $1.75M^2 + 2.25*M$ multiplications for $P(k)$. Additionally, the power method [133] is needed to find the eigenvector of equation (4.66). In this case, at least M^2 complex multiplications are needed for each iteration by using power method. Total complex multiplications for Auto-SCORE algorithm is $(3.25+n)M^2 + 2.75M$, where n is the number of iterations needed to solve equation (4.66) with power method which is depends on the distribution of eigenvalues of (4.66).

4.4.4 Two-mode algorithm

In application, it is possible to combine the DMI with the PHASE algorithm to achieve better output SINR than by using PHASE alone. For instance, at the beginning of adaptation, PHASE is used to start up blindly. After some point, say $n_0=40$, when the output SINR is reasonably high and the BER (bit error rate) is less than 10^{-3} , DMI takes over, using the estimated data symbols as a reference to adapt the weighing coefficient sample by sample.

Let's assume that at n_0 , PHASE algorithm is shifted to DMI. Ideally, the following equation can be used for update the optimum weighting vector.

$$\hat{w}_T(n_0 + 1) = \hat{w}_P(n_0) + \Delta \hat{w}_{DMI}(n_0) \quad (4.68)$$

where subscript T denotes the two-mode algorithm, $\hat{w}_P(n_0)$ is optimum weighting vector

of PHASE algorithm up to point n_0 .

$$\Delta \hat{w}_{DMI}(n_0 + 1) = \frac{P(n_0) X(n_0 + 1) \left(\hat{d}(n_0 + 1) - \hat{w}_D(n_0 + 1)^H X(n_0 + 1) \right)^*}{1 + X(n_0 + 1)^H P(n_0) X(n_0 + 1)} \quad (4.69)$$

$\hat{d}(n_0 + 1)$ is the estimated data and the notations in section 4.4.3 are used here. If the estimated data sequence is correct, then equation (4.69) is the same as the second term in equation (4.61) for recursive DMI algorithm and

$$\hat{w}_T(n_0 + L - 1) \rightarrow \hat{w}_{DMI}(n_0 + L - 1) \quad (4.70)$$

when $L \gg 1$. However, as mentioned in Section 4.4.1, the weighting vector from the DMI algorithm different from the weighting vector from PHASE algorithm by a arbitrary complex scale which means that using equation (4.69) doesn't guarantee that (4.71) holds because the phase difference of weighting vectors between DMI and PHASE algorithms. In order to avoid this problem, the following procedure is used.

1. First, at $k = n_0$, L data $\{\hat{d}(n_0 - i), i = 0, 1, 2, \dots, L - 1\}$ are estimated using PHASE algorithm.

2. Treating the L data as training sequence and calculate the cross-correlation between the received data and the training sequence by equation

$$\hat{r}_{x\hat{d}}(n_0) = \sum_{i=0}^{L-1} X(n_0 - i) \hat{d}(n_0 - i) \quad (4.71)$$

3. Calculate the weighting vector

$$\hat{w}_T(n_0) = P(n_0) \hat{r}_{x\hat{d}}(n_0) \quad (4.72)$$

4. Replacing $\hat{w}_P(n_0)$ in (4.69) by (4.73) to update the weighting vector

One simulation run of the two-mode algorithm which combine DMI and PHASE algorithms is shown in Figure 6, where $L=6$ is used. It indicates that there is a significant improvement in both convergence speed and output SINR. The simulation parameters are the same as shown in Table 1. The problems associated with two-mode algorithm is when to switch the algorithm. It is obvious that if the switch is too early, the performance will not be good due to error of estimated data.

It should be noted that differential phase modulation must be used with PHASE

Figure 4.4. One simulation run for comparison of DMI, PHASE and Two-mode algorithms. Shift at $n=40$, SNR = 20 dB, Non-fading.

algorithm, since only phase differences are significant due to the fact that all blind algorithms will be subject to a phase ambiguity.

4.5 The Sensitivity of Proposed Algorithm to the Perturbation of Cyclostationarity.

So far, we have assumed that the frequency of interest α is known and generated exactly at the receiver [17,20,95,96,107,108], when the cyclic-autocorrelation functions (4.41) or (4.55) are calculated. No attention has been paid to the situation when α isn't

known exactly. However, there are three types of factors which limit us to obtain the exact α in practice. First, we may need to estimate the signal periodicity from the signal received before implementing the cyclostationary signal processing, if this parameter is not available. The estimation will result in some error which, in turn, affects the performance of signal processing later on. Second, at the receiver, a specific frequency is needed to be generated by the frequency generator to produce the reference signal for the purpose of demodulation, which probably will bring some errors comparing to the transmitted frequency. Third, there exists the Doppler shift in the signal received. All three factors will influence the system performance.

Generally, the actual frequency of the desired user signal can be expressed as

$$\hat{\alpha} = \alpha + \Delta\alpha \quad (4.73)$$

In turn, the cyclic covariance matrix of received signal vector $X(n)$ due to the perturbation of periodicity is given by

$$R_{xx}^{\hat{\alpha}} = R_{xx}^{\alpha} + \Delta R_{xx}^{\alpha} \quad (4.74)$$

where R_{xx}^{α} is the cyclic correlation matrix without periodical perturbation, and ΔR_{xx}^{α} is the change in R_{xx}^{α} due to the perturbation of periodicity. It is of interest to know how the output SINR of antenna array changes with the perturbation of cyclostationarity of received data for a given modulated transmission signal. This problem is of particular interest in practical implementation, since α is never exactly known.

For the BPSK signal defined by (4.45), it proved, in Appendix E, that

$$R_{ss}^{\hat{\alpha}} = \frac{1}{N} \frac{1 - e^{j2\pi\Delta\alpha N}}{1 - e^{j2\pi\Delta\alpha}} \quad (4.75)$$

where it is assumed that the $\Delta\alpha$ is constant during the consideration period of N . Although $\Delta\alpha$ may be a random variable due to random Doppler shift, this assumption will provide an idea how much $\Delta\alpha$ is allowable for a given performance. The magnitude of above equation is

$$\begin{aligned} |R_{ss}^{\hat{\alpha}}| &= \left(\frac{1}{N}\right) \sqrt{\frac{|1 - \cos 2\pi\Delta\alpha N|}{|1 - \cos 2\pi\Delta\alpha|}} \\ &= \left(\left(\frac{1}{N}\right) \left(\frac{|\sin \pi\Delta\alpha N|}{|\sin \pi\Delta\alpha|}\right)\right) = \frac{1}{\pi\Delta\alpha N} |\sin \pi\Delta\alpha N| \end{aligned} \quad (4.76)$$

In next chapter, the simulation results are presented to demonstrate how the SINR of array output changes with the change of $\Delta\alpha$.

Chapter 5. Simulation Results

In this Chapter, simulation examples are presented to compare the properties of the algorithms discussed in Chapter 3 and Chapter 4. The comparison of outage probability between TDMA and proposed CTDMA system are compared in section 5.7.

5.1 Introduction

The following assumptions and parameters are used in this chapter. It is assumed that all the signals received are perfectly synchronized in the sense of having the same symbol rate and right sample timing. In the DMI algorithm, it is assumed that the reference signal at the receiver is the same as the signal transmitted. A circular 4-element array with an element spacing equal to half a wavelength is investigated. The discrete baseband carrier frequencies (BCFs) of user and interferences are $0/48, 1/48, \dots$ of the transmission bandwidth respectively. The carrier frequency spacing Δf is $1/48$. For instance, if the bandwidth of each user's channel is 48 kHz, then equivalently, the carrier frequency of each user has at least 1 kHz separation from others. Generally, the larger the spacing between two baseband carrier frequencies, the better the performance of the system. The received signal is of the form

$$X_i(t) = s_i(n)p(t-nT)\alpha_i \exp[j(2\pi f_i t + \theta_i)] \quad (5.1)$$

where, $\{s_i(n)\}$ is the real data sequence, $p(t)$ is a pulse waveform defined over $[0, T]$ (T is a bit duration), f_i is the baseband carrier frequency, α_i and θ_i are Rayleigh and uniform random variables respectively. The performances of algorithms are evaluated by output SINR of the array which is defined as

$$SINR(w) = \frac{w^H P_0 A_0 A_0^H w}{w^H R_{nn} w} \quad (5.2)$$

where

$$R_{nn} = \sum_{i=1}^N P_i A_i A_i^H + \sigma^2 I \quad (5.3)$$

P_0 , P_i , and σ^2 are the signal, interferences and noise powers respectively. Simulations are

run under the non-fading and fading cases. In case of non-fading, SINR is obtained for given specific DOAs of users. In the case of fading, the magnitude and phase of the signal received at each antenna element are a Rayleigh and uniform random variable respectively, and SINR is obtained by averaging the results from the random magnitude and phase of received data for different users. All simulation results related to SINR are averaged over 1000 simulation runs. There are two types of fading channels used in this Chapter. The normalized doppler frequency of fading-I and fading-II channels are $10/48000$ and $10/24000$ respectively, e.g. 10 Hz for 48 kHz, 10 Hz for 24 kHz channel bandwidth respectively. In all figures, the x-axis starts at the 10th sample, since the performance of SCORE and PHASE is quite poor if the number of samples used for the adaptation (N) is less than 10. In Section 5.2 and 5.7, in addition to Rayleigh fading, a Rayleigh plus Lognormal fading is also studied by simulation. Typical values of lognormal variance 6 and 12 dB for indoor wireless systems are used.

5.2 Comparison of DMI, SCORE, M-SCORE, and PHASE

5.2.1 Comparison of DMI with PHASE

Among the four algorithms: DMI, SCORE, M-SCORE and PHASE algorithms, DMI is called a non-blind algorithm, since the training sequence is needed in order to estimate the DOA of the desired user as shown in Chapter 4. It is expected that DMI will give the best performance. We are interested in knowing how close is the performance of blind algorithms to that of DMI, how long a training sequence is needed for DMI, and how many samples are necessary for PHASE algorithms to deliver acceptable performance. The comparisons between the DMI and PHASE are presented in Figure 5.1 where the DOAs of desired user and one interferer are 50° and 165° respectively. In all cases, the PHASE performance approaches steady state after about 150 samples. DMI needs about 14 samples to reach the steady state for $\text{SNR} = 20$ dB. However, in case of $\text{SNR} = 12$ dB and fading, DMI needs a longer training sequence for convergence. It is shown that the performance is sensitive to the input SNR, since the array can not do anything against the noise. Ideally, the array can reject the interference completely, the maximum achievable SINR is input

SNR plus the array gain $10 \cdot \log_{10}(M)$ (6 dB for $M=4$). In our case, if $\text{SNR} = 12$ dB, then output $\text{SINR} = 12 + 6 = 18$ dB; if $\text{SNR} = 20$ dB, $\text{SINR} = 20 + 6 = 26$ dB. The SINRs of DMI obtained from the simulation are very close to the maximum achievable SINR in case of non-fading. The results indicate that, within a few dB of sacrifice for output SINR and longer adaptive time, the blind algorithm can be used to replace the non-blind algorithm to improve the spectrum efficiency. It is also noticed that the performance degrades with the increase in fading rate.

5.2.2 Comparison of SCORE, M-SCORE and PHASE

The comparisons of SCORE, M-SCORE, and PHASE are presented in Figure 5.2. The performances of PHASE and M-SCORE are very close for the non-fading case, and give better performance than that of SCORE. In case of fading, PHASE provides the best performance. SCORE represents the worst case. Carefully checking the algorithm, it is found that the problem related to the SCORE is that, in our scenarios, the top two eigenvalues of equation (3.28) will be very close. Since the rank of the cyclic covariance matrix is less than M due to the cyclic correlation operation, the eigenvalues are sensitive to input data. In some situations the algorithm will pick up the wrong eigenvector as the optimum weighting vector, which degrades the system performance considerably. Although both M-SCORE and PHASE give the close performance in non-fading case, PHASE provides the simpler and faster method. In the rest of chapter, only the performances of DMI and blind PHASE algorithms will be studied in simulation.

5.3 Sensitivity of Cyclic-autocorrelation and Array SINR

As mentioned in Section 4.5, there are three kinds of errors which prevent us from getting the exact frequency of interest α . That is, Doppler frequency shift, frequency estimation error and frequency generation error. Since the cyclic correlation operation plays an important role in this thesis, we first study the sensitivity of cyclic correlation operation of a signal to the perturbation of its periodicity. Then the simulations on the robustness of array output SINR are demonstrated. Through simulations, we try to provide some insight on how much error the system can tolerate for the given time period and frequency offset. In simulation, we assume that user #1 is a desired user and f_1 in (5.1) is

figure 5.4 The change of cyclic-autocorrelation functions with the perturbation of cyclostationarity. Fading channel case.

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PM-1 3½"x4" PHOTOGRAPHIC MICROCOPY TARGET
NBS 1010a ANSI/ISO #2 EQUIVALENT

Figure 5.1 The comparison between DMI and PHASE algorithms

Figure 5.2 Comparison of SCORE, M-SCORE and PHASE algorithms

fixed. At the receiver, the received signal is

$$r_1(t) = X_1(t) \exp(j2\pi\hat{\alpha}t) \quad (5.4)$$

Ideally, $\hat{\alpha} = \alpha = 2f_1$. Now we show, under the situations that $\hat{\alpha} = \alpha + \Delta\alpha$, $\Delta\alpha = 1/2 * \Delta f$, $1/4 * \Delta f$, $1/8 * \Delta f$, and $1/16 * \Delta f$ with $\Delta f = 1/48$, how the magnitude of the cyclic correlation

$$R_{uu}^{\alpha}(0) = \langle X_1(t) r_1(t) \rangle_N \quad (5.5)$$

changes with different α , where N is the total number of samples for time averaging. The analytical result of equation (5.5) is presented in Appendix E for the non-fading signal. The simulation parameters are listed in Table 5.1. With the same assumptions made in Section 5.1 for system parameters, Figure 5.3 and 5.4 present simulation results for fading and non-fading cases respectively. Only fading-1 channel is simulated in Figure 5.2 for SIR=0 dB. Since the fading rate is quite small, both fading and non-fading channels give almost the same performance. It is seen that, if $\alpha \neq 2f_1$, R_{uu}^{α} will attenuate with N . The larger the $\Delta\alpha$, the faster is the decay. For example, in GSM system, a time slot consists of 148 bits, the adaptation time must be less than this time period. The faster the algorithm converges, the larger perturbation in the periodicity the system can tolerate.

Table 5.1 Simulation parameters (SNR = 20 dB)

user #	DOA	Relative Power	baseband carrier freq.
1	60°	0 dB	1/48
2	165°	0 dB	2/48
3	220°	0 dB	3/48

Figure 5.3 and 5.4 present the change of cyclic-autocorrelation functions with the perturbation of cyclostationarity for the desired signal received at one antenna element. It is noted that, when $\Delta\alpha = \Delta f$, the cyclic-autocorrelation function of received signal becomes that of adjacent interferers. Generally an antenna array can combat a large perturbation of cyclostationarity, when the minimum frequency offset is large. However, the spectrum efficiency will be lowered by increasing the frequency offset as shown in section 5.7. Figure 5.5 and 5.6 demonstrate how output SINRs of array change with

Figure 5.3 The change of cyclic-autocorrelation functions with the perturbation of cyclostationarity. Non-fading channel case.

figure 5.4 The change of cyclic-autocorrelation functions with the perturbation of cyclostationarity. Fading channel case.

perturbation of the cyclostationarity in the cases of Rayleigh fading and Rayleigh plus Lognormal fading respectively. Here, as an example, only PHASE algorithm is used. From the simulation results, it is clear that the output SINR of array is determined by the magnitude of cyclic-autocorrelation function of desired user. The fluctuation of SINR in Figure 5.5 and 5.6 are contributed by the change of the cyclic-autocorrelation function of interferers as shown in next section.

5.4 Convergence of Cyclic-correlation with different BCF offsets

In the last section, results on how the cyclic autocorrelation of a signal changes with perturbations in its periodicity were presented. In the appearances of noise and interference, Chapter 4 shows that the system performance depends on how fast the cyclic-correlations of noise and interference approach zero at the frequency separation α . The simulation results presented in Figure 5.7 and 5.8 show how the cyclic autocorrelations of user change with time and BCF offsets. $u_1(t)$ and $r_1(t)$ are given separately in (5.4) and (5.5);

$$\begin{aligned} X_2(t) &= s_2(t) p(t - nT) \alpha_2 \exp[j(2\pi f_2 t + \theta_2)] & r_2(t) &= X_2(t) \exp(j2\pi \alpha t) \\ X_3(t) &= s_3(t) p(t - nT) \alpha_3 \exp[j(2\pi f_3 t + \theta_3)] & r_3(t) &= X_3(t) \exp(j2\pi \alpha t) \end{aligned} \quad (5.6)$$

where $\hat{\alpha} = \alpha = 2f_1$, $s_2(t)$ and $s_3(t)$ are the interference data sequences, f_2 and f_3 are the BCFs of the interferences, α_2 , α_3 and θ_2, θ_3 are independent Rayleigh and uniform random variables within $\{0, 2\pi\}$ respectively. It demonstrates that the larger the BCF offset of interfering user from the desired user, the faster the cyclic-autocorrelation of noise and interference approach to zero. Again, only one fading-I channel is simulated in Figure 5.8. Since the magnitude of the channel changes with time, the magnitude of cyclic-autocorrelation also changes.

Figure 5.9 presents how the system performance in terms of SINR changes with different BCF spacings. The frequency offset spacings are 1/48 and 1/96 respectively. The DOAs of user and interferer are 50 and 165 degree respectively. It is shown that the algorithm with larger Δf approaches to the steady state faster. Generally, for larger

Figure 5.5. Array output SINR with perturbation of the cyclostationarity in case of Rayleigh fading

Figure 5.6. Array output SINR with perturbation of cyclostationarity in case of Rayleigh plus Lognormal fading

baseband carrier frequency offset, the R_{uu}^O will be more accurate and system performance is better based on the finite data collection. Obviously, the faster convergence rate is achieved at the expense of spectrum efficiency. In application, we have to trade off between the spectrum efficiency and adaptive time for required system performance, since the larger frequency offset will reduce the spectrum efficiency.

5.5 The effect of different DOAs of interferences

Theoretically, the interference can be completely rejected if the number of elements is larger than the number of users. However, in practice, we only can null the interference to a certain extent. The null depth will depend on the interference power [87], the noise power, and the estimation accuracy of DOA of desired user and the number of antenna elements. It is seen, from the equations (4.11) and (4.12), that system performance also relates to the DOA of interference. It is clear from (4.37) how d , the correlation coefficient (CC) between two DOAs, affects the system performance. The simulation is used here to corroborate the conclusions. Suppose there are four users with their DOAs 50, 135, 165 and 230 degrees respectively. Let the user with DOA 50 degree be the desired user and others are treated as the interference, then the CCs between the desired user and the interferences are 0.0008, -.2393, and -.6880 respectively. Figure 5.10, 5.11 and 5.12 show the results of comparisons between PHASE and DMI for interfering users with different DOAs. Figure 5.13 presents the results of the PHASE for different DOAs of interferences. As shown in these Figures, if d is small, the performance of PHASE will be close to that of DMI. If d is larger, the performance of PHASE will depart from that of DMI. The steady state performance of PHASE and DMI is quite close for small d . It is also noticed that the larger the d , the bigger the fluctuation of the output SINR for PHASE. This phenomenon can be explained from (4.37). There exists some fluctuation of cyclic correlation as shown in Figure 5.3 and 5.4. For small d , the second term in the right side of (4.37) has no impact on the output SINR once the PHASE reaches its steady state. However, for larger d , the second term is not negligible, the fluctuation in SIR^{α} results in the magnitude change of output SINR.

Figure 5.7 The cyclic-autocorrelation functions of desired user and interfering users with different baseband carrier frequencies. Non-fading channel case

Figure 5.8 The cyclic-autocorrelation functions of desired user and interfering users with different baseband carrier frequencies. Fading channel case.

Figure 5.9 Comparison between two different BCF offsets

Figure 5.10 Comparison PHASE with DMI in case of two users.

Figure 5. 11 Comparison PHASE with DMI in case of two users

Figure 5.12 Comparison PHASE with DMI in case of two users

Figure 5.13 Comparison among interferences with different DOAs

5.6. Properties of PHASE Algorithm

As we mentioned in Chapter 4, with an M-element antenna array, one of the branches can be chosen as the reference branch, and the optimum weight vector is obtained in the MMSE sense. The M weight vectors can be combined together to improve SINR. The simulation results of the PHASE algorithm are presented in Figure 5.14 and 5.15 for the non-fading and fading-I cases respectively. It is shown that the larger the number of weighting vectors combined, the better is the performance. The combined weighting vector can provide better performance because it can combat fading and increase the estimation accuracy of desired DOA. The comparison of SINR(dB) between EGC and MRC presented in Section 4.4 is shown in Table 5.2. The simulation parameters are the same for EGC and MRC as shown in Table 5.1. It indicates that, in cases of non-fading and small fading rate, EGC provides the slightly better performance. If the fading rate increases, the MRC gives slightly better performance. In the examples presented in this thesis, only MRC is used. It should be noted that the solid line in Figure 5.14 and 5.15 are also the performance of LS-SCORE.

Table 5.2 Comparison SINR (dB) between arithmetic and weighted combining (SIR=-3 dB)

Fading rate	Equal gain combining		Maximum ratio combining	
	SNR = 12 dB	SNR = 20 dB	SNR = 12 dB	SNR = 20 dB
0	17.0193	24.3606	17.0033	24.2307
10/960,000	15.6763	21.4857	15.6990	21.3889
10/480,000	15.6012	20.4401	15.7864	21.1670
10/240,000	12.2093	15.5244	12.8428	16.6804

SNR = 20 dB. SIR = -3 dB, Non-fading channel, PHASE

Figure 5.14. The effect of the number of reference antennas

SNR = 20 dB, SIR = -3 dB, Fading-I, PHASE

Figure 5.15. The effect of the number of reference antennas

5.7 Comparison between TDMA with proposed CTDMA in a real cellular scenario

5.7.1. Introduction

Since the spectrum is limited and therefore a very valuable resource, many efforts have been made to find ways to use the spectrum efficiently, that is, to support as many users as possible for a given service quality and spectrum bandwidth. For this purpose, high capacity mobile radio systems with TDMA or CDMA are proposed to improve the spectrum efficiency [46].

In this section, based on the cyclic signal processing techniques, a modified TDMA version called Cyclic-TDMA (CTDMA) system is proposed. The research indicates that the CTDMA can achieve considerable improvement in spectrum efficiency over that of conventional TDMA.

This section is organized as follows. Section 5.7.2 discusses the configuration of the cellular radio system. The channel assignment and capacity example are presented in section 5.7.3. The comparison of the channel capacities of TDMA and Cyclic-TDMA are made in section 5.7.4.

5.7.2 Cellular System Configuration

Suppose the service area of a cellular radio system is divided into a regular array of hexagonal cells as shown in Figure 5.16. These cells are grouped in identical clusters, where each cluster occupies the total bandwidth available to the mobile radio system.

For reverse communication (mobile to base station) in a conventional TDMA or FDMA system, there is no interference within the desired cell, since each user is orthogonal to others either in time or frequency domain. There are six co-channel interferences from the neighbor cells in the first tier as shown in Figure 5.16 with the number labeled 1 to 6, where the cluster size k equals to 4. The cell labeled number 0 is treated as a desired cell, and cells with number 1 to 6 are interference cells, where the number 1 to 6 indicates the amount of frequency offset.

At the base station in cell 0, the receiver receives the signal from the desired user

within the cell, and the interference signals from the users in the co-channel cells 1 to 6 (neglecting interference from outer tiers). The system performance will depend on how the system rejects the CCI, how the neighbor cells are loaded, and the characteristics of the propagation channel. In order to take advantage of cyclic signal processing techniques[1.2], we modify the channel assignment to make the system reject more interferences and improve the system capacity.

5.7.3 Channel Assignment and Capacity Example

In order to compare the radio channel capacity between a conventional TDMA scheme and

the proposed Cyclic-TDMA scheme, consider a total system-bandwidth of $B_t=1.25\text{MHz}$. Each user has a channel bandwidth $B_c=30\text{kHz}$ with three time slots. For a cell reuse factor of $k=4$, the maximum radio capacity (neglecting CCI) is given by

$$m_{TDMA} = \frac{3 \times B_t}{k \times B_c} = \frac{3 \times 1.25 (\text{MHz})}{4 \times 30 (\text{kHz})} = 31 (\text{users/cell}) \quad (5.7)$$

Alternatively, we also can distribute the channels in another way so that all channels of interferences at the six co-channel cells have some frequency offset from the channel of the desired user. In the proposed CTDMA scheme, one of channel assignment schemes is that seven channels in cells 0 to 6 are evenly distributed over the specific spectrum range. For example, using the same system parameter as for TDMA, the channel bandwidth of the desired user is 30 kHz and covers the spectrum from 0 to 30 kHz, the channels each co-channel user in cells 1 to 6 cover the spectrum from the 1 to 31 kHz, 2 to 32 kHz..... and 6 to 36 kHz. In this way, each channel has, at least, 1 kHz offset from the other channels in the first and second tiers as shown in Figure 5.16. The radio channel capacity of CTDMA system is

$$m_{CTDMA} = \frac{3 \times B_t}{K \times B_c} = \frac{3 \times 1.25 (\text{MHz})}{4 \times 36 (\text{kHz})} = 26 (\text{channels/cell}) \quad (5.8)$$

At a glance, comparing (5.8) with (5.7), the radio channel capacity of C-TDMA is reduced by 5 users per cell. But remember that the real radio channel capacity must take the C/I ratio into account. The key issue is whether the TDMA can provide the required C/

Figure 5.16 The channel assignment of a cellular system with $k=4$. For TDMA system, each user in cells labeled 0 to 6 shares the same channel. For CTDMA system, each user in cells labeled 0 to 6 has at least 1 kHz frequency offset from other users as used in simulation

or not for the given cluster size. As we mentioned in chapter two, it is not the channel radio capacity but the spectrum efficiency that is to be maximized. The comparisons among different channel assignment schemes make sense if and only if the conditions (for example, outage probability $<10^{-3}$) based on which the system are operated are also considered. The simulation show that, under the same conditions, C-TDMA system performance in terms of SINR and outage probability is better than that of TDMA, which makes the spectrum efficiency of C-TDMA higher than that of TDMA system. This will be shown in next section.

Figure 5.16 only indicates one of many possible ways of channel assignment, in which the cochannel users at first and second tiers have the frequency offset with desired user. If only the cochannel interferers at first tier are of concern, the channel assignment scheme in Figure 5.17 can be used. In this case, the capacity in equation (5.9) is 29. Theoretically, the channel capacity could be improved even more if we distribute all the channels with the some frequency offset over whole spectrum range as mentioned in [15]. However, this scheme requires a lot of antenna elements. In practice, considering the implementation difficulty, the computing time, we focus on the two channel assignment schemes mentioned above in our investigation.

5.7.4 Simulation Results

In this section, a circular array with 8 elements is used, which guarantees that the number of elements in the array is larger than that of desired user plus the interferences so that the array has enough freedom to reject the interferences. In most previous studies, only a two dimensional scenario is considered. Here a three dimensional configuration of antenna array and users is considered. We assume that the base station is fixed on the ceiling which has 3 m height from the floor. The cell radius is 25 meters. In simulations, the worst scenario is considered, that is, the desired user is located at the boundary of desired cell, the interferences are located at the boundaries of their cells, and all interferers are active. One of the interferers has the same azimuth as the desired user. The azimuths of the other interferences are evenly distributed over $(0, 2\pi)$. The elevations of interferences

Figure 5.17 The channel assignment of a cellular system with $k=4$. For TDMA system, each user in cells labeled 0 to 2 shares the same channel. For CTDMA system, each user in cells labeled 0 to 2 has at least 1 kHz frequency offset from other users.

are calculated according to their geometry. The discrete BCFs of one user and six interferences are $0/48$, $2/48$, ..., and $6/48$ respectively. The normalized fading rate is $10/240000$. The simulation result are obtained over averaging 1000 channels. The following three situations are investigated:

1. Rayleigh fading with six co-channel interferences at the first tier.
2. Rayleigh fading plus Lognormal fading with variance 6 dB. and interferers at the first tier.
3. Rayleigh fading plus Lognormal fading with variance 12 dB. and interference at the first and second tier

The reason we consider the effect of interferences from second tier is that, with lognormal variance as high as 12 dB, the interference level of composite 12 users in the second tier is comparable to that at the first tier. The simulation results are presented in Table 5.3 for SINR and Table 5.4 for probability for various thresholds.

Table 5.3 Array output SINR (dB) (SNR=40 dB)

	TDMA			CTDMA		
	(1)	(2)	(3)	(1)	(2)	(3)
Input SINR						
Mean	11.2	10.3	6.56	11.2	10.3	6.56
Std. Dev.	.863	3.31	7.44	.863	3.31	7.44
Output SINR						
Mean	20.7	19.4	12.1	26.4	27.2	18.1
Std. Dev.	1.41	4.29	10.1	1.04	3.29	7.66

Table 5.4 Outage probability (SNR=40 dB)

Outage Prob.	TDMA			CTDMA		
	(1)	(2)	(3)	(1)	(2)	(3)
p(x<6 dB)	0	.005	.228	0	0	.077
p(x<8 dB)	0	.007	.278	0	0	.102
p(x<10 dB)	0	.018	.377	0	0	.137
p(x<12 dB)	0	.049	.458	0	0	.190
p(x<16 dB)	.001	.199	.617	0	0	.342
p(x<18 dB)	.032	.363	.696	0	.002	.386

The results show that the performance of CTDMA is better than TDMA. For small lognormal variance, CTDMA provides the required system performance (outage probability less than 10^{-3}) even in the worst case. Since only the worst case scenario is simulated here, it is only give the bound of system performance but the practical system performance. More simulations will be conducted in the future for practical scenarios. But it is noted that the lognormal variance does affect the system performance considerably.

Table 5.5 presents the simulation results for outage probability in case of SNR = 20 dB. As

Table 5.5 Outage probability (Input SNR = 20 dB)

Outage Prob.	TDMA			CTDMA		
	(1)	(2)	(3)	(1)	(2)	(3)
p(x<6 dB)	0.011	0.166	0.526	0.001	0.021	0.196
p(x<8 dB)	0.016	0.204	0.553	0.003	0.028	0.241
p(x<10 dB)	0.028	0.240	0.586	0.003	0.042	0.281

Table 5.5 Outage probability (Input SNR = 20 dB)

Outage Prob.	TDMA			CTDMA		
	(1)	(2)	(3)	(1)	(2)	(3)
$p(x < 12 \text{ dB})$	0.059	0.290	0.621	0.007	0.064	0.323
$p(x < 14 \text{ dB})$	0.123	0.356	0.653	0.011	0.094	0.388
$p(x < 16 \text{ dB})$	0.217	0.438	0.687	0.032	0.136	0.443

expected the input SNR affects the performance considerably.

5.8. Comparison Adaptive Array with Sectored Array

In this thesis, only adaptive array is considered for its performance to reject interference and combat fading based on the space diversity. Alternatively, there is another configuration -- a sectored antenna array, which can also be used to reject the interference if the angular separation of the interference is large, and reduce the time delay spread if different path are from different sectors.

Generally speaking, adaptive array can be used to reject cochannel interference effectively. For larger time delay spread ($\text{rms} > 0.2 T$, where T is a bit duration), the array cannot effectively reduce the ISI to desired level except with a large number of antenna array elements. A sector antenna array can be used to reject the co-channel interference and ISI, and is simple from the implementation point of view. However, the performance of sector array depends on the geometry of communication environment [79].

In case of frequency-selective channel, the comparison of outage probability among the systems with one omnidirectional antenna, one omnidirectional antenna plus DFE (decision feedback equalizer), six-sector antenna array, and six-sector array plus DFE are made in [79].

Figure 6.3. Comparison of performances of DMI and PHASE. SNR = 20 dB

Figure 5.18 Two different antenna patterns. a) Nonoverlap pattern. b) Overlapped pattern without sidelobes.

The simulation results for comparison of adaptive array with sector array are shown in Figure 5.19. It is noted that adaptive antenna array provides the best performance. This is due to the fact that after diversity combining, the desired signal to interference plus noise ratio is improved by combating fading and rejecting interference. For the sectored antenna array, although five out of six interfering signals are rejected for a specific sector, due to fading effect, the fluctuation of SINR is greater than that of SINR in case of adaptive array. This is why there is a long tail of outage probability for sector array. It also indicates that there is not much difference in output SINR between nonoverlap and overlapped sector arrays. There is about 2 dB and 1.5 dB difference between nonoverlap antenna pattern array and overlapped antenna pattern array for model i) and ii) respectively. Four curves give similar performance.

It should be mentioned that an array with fixed pattern is easy to implement. It effectively reduces the effect of multipath and reject the interference provided that these paths and interfering users are coming from different sectors. However, a tracking algorithm is needed to select the sector with best received signal.

With the adaptive antenna array, the optimum weight vector has to be calculated and updated according to the change rate of communication environments. Compared to the former case, intensive computation is needed.

The results shown in this section only provides us a feeling about how both adaptive and sectored array deal with flat fading and interference. The channel models used are also simplified models. In order to make a fair comparison, it is necessary to consider the real communication environment, since performance of sector array heavily depends on the characteristics of channel model, the DOAs of multipath and interfering users.

5.9 Summary

The work presented in this Chapter provides an insight to system designers on how to use cyclostationarity of transmission signal to improve the system performance by reducing the interference and increasing the spectrum efficiency.

Figure 5.19 Comparison of adaptive array with sectored array for different channel models

Chapter 6. The Performance Analysis of Adaptive Antenna Array with a Large Number of Interfering Users

6.1 Introduction

The antenna array is an important technique to combat fading and interference. It allows transmission at high bit rate in indoor wireless communication [80,81]. In the papers published on antenna diversity, it is often assumed that there are fewer users than antenna elements. Under this assumption the system capacity can be improved by M fold or the system can be made to tolerate $M-1$ interferers from other systems with M branch antennas[126]. Few research works have reported the case where the number of users is greater than that of antenna elements. The influences of diversity order and number of dominant interferers for $M=2$ antenna elements and one dominant interferer were analyzed by Compton[125]. Clark [14] studied the situation of $M=2,3,4$ antenna elements and up to three dominant interferers by simulation. Most studies, where the number of interfering users is larger than the antenna elements, treat the weak interferers as additive noise to simplify analysis. Some simulation results are reported in [14].

However, in a real cellular mobile scenario, though the magnitudes of some of the interfering users are small, it is more reasonable to assume that the number of antenna elements is less than the desired user plus the number of interferers including the interfering users from the second tier. Also, in case of multipath, an antenna array will treat each path of each interfering user as an interference. It is of interest to know how an antenna array responds to this environment, and how valid is the commonly-made assumption to lump the weak interferences into an equivalent additive Gaussian noise.

To the author's knowledge, very little is reported on the analysis and simulations of the behavior of antenna array in the case when the number of interferers is equal to or larger than the number of antenna elements. In this Chapter, we will study the response of an antenna arrays and evaluate system performances under arbitrary numbers of antenna

elements and users.

The analysis and simulation results presented in this Chapter will provide the system designer with tools to predict the performance of the array in the case that the total number of users is more than the number of antenna elements. Furthermore, the performances of antenna arrays using the DMI (Direct Matrix Inversion) [24] and blind PHASE algorithm [127] are compared. In this paper, M denotes the number of antenna elements in array, N the number of interferers. Therefore the total number of users, desired user plus interferers, is $N+1$.

The rest of the Chapter is organized as follows: A brief review of the previous work on the case of $M > N$ is presented. Some details on concepts, notations, and background knowledge in antenna array are also introduced. The analysis of the influence of the channel diversity with $M \leq N$ is presented in section 3. In section 4, the simulation results demonstrate the validity of the analysis presented in section 3. The Chapter concludes with a summary.

6.2 Previous work on performance of antenna array for $M > N$

It is well known that an M -element antenna array can improve the system capacity by M fold or tolerate $M-1$ interferences when $M > N$ [121,126]. For example, in an $N=M$ user environment with no multipath, the covariance matrix of array received signal may be written

$$R_{xx} = \langle X(n) X^H(n) \rangle_N = P_0 A_0 A_0^H + \sum_{i=1}^{M-1} P_i A_i A_i^H + \sigma^2 I = P_d A_d A_d^H + R_{nn} \quad (6.1)$$

where P_0 and A_0 are the power on each array element and DOA of the desired signal respectively. P_i and A_i ($i=1,2,\dots,M-1$) are the powers and DOAs of $M-1$ interferers respectively, and R_{nn} is called the interference plus noise matrix. The optimum weighting vector is, under the minimum mean squared error criterion,

$$w_{opt} = R_{xx}^{-1} A_0 = k_1 R_{nn}^{-1} A_0 = k_2 P A_0 \quad (6.2)$$

as shown in [24,121]. Here k_1 and k_2 are two constants. Matrix P is called projection matrix which projects any vector onto the subspace orthogonal to the vectors A_i ($i=1,2,\dots,M-1$). A detailed discussion of P is given later in this section.

In case of no interferer, the covariance matrix (6.1) may be rewritten as

$$R_{xx} = P_0 A_0 A_0^H + \sigma^2 I \quad (6.3)$$

the optimum weighting vector is

$$w_{opt} = R_{xx}^{-1} A_0 = \frac{1}{MP_d + \sigma^2} A_0 \quad (6.4)$$

The output SNR is given by

$$SNR = \frac{w_{opt}^H P_0 A_0 A_0 w_{opt}}{w_{opt}^H \sigma^2 w_{opt}} = M \frac{P_0}{\sigma^2} \quad (6.5)$$

i.e. the SNR is proportional to M, the number of antenna elements.

In the presence of interference, another way to represent the projection in (6.2) is to use the representation in [121]

$$Q = [A_1 \mid A_2 \mid \dots \mid A_{M-1}] \quad (6.6)$$

as in equation (6.1) for the vectors. The matrix

$$\tilde{P} = Q(Q^H Q)^{-1} Q^H \quad (6.7)$$

is a projection matrix which projects any vector into the subspace spanned by the $M-1$ vectors A_i ($i=1, 2, \dots, M-1$) by setting to zero any component which lies outside it. Conversely, the complementary projection

$$P = I - \tilde{P} \quad (6.8)$$

has the effect of projecting any vector onto the subspace orthogonal to vectors A_i ($i=1,2,\dots,M-1$). When the projection P operates on A_0 in equation (6.2), it can be thought as generating a new coordinate $w_0=w_{opt}$. Thus w_0 is orthogonal to $A_1, A_2, \dots, A_{M-1}$:

$$A_i^H w_0 = 0, \quad i = 1, 2, \dots, M-1 \quad (6.9)$$

However,

$$A_0^H w_0 \neq 0 \quad (6.10)$$

It shows that normally there is some residual amplitude gain for the desired signal. In this sense, the system can tolerate $M-1$ interferers. It should be noted that if equation (6.9) holds, the system can completely reject the $M-1$ interferers, provided the *INR* (interference to noise ratio) is large. In case of low *INR*, the system can not completely reject the interferences and the performance will show some degradation, the amount of which depends on specific *INR* and DOAs of interferers. The detailed discussion on how the output *SINR* of array related to *INR* and DOA of interferer is given in Chapter 4.

The signal to interference plus noise ratio (*SINR*), using the results in equation (6.1) and (6.2), is given by

$$\begin{aligned} SINR(M-1) &= \frac{w_{opt}^H P_0 A_0 A_0^H w_{opt}}{w_{opt}^H (R_{xx} - P_0 A_0 A_0^H) w_{opt}} \\ &= A_0^H R_{nn}^{-1} A_0 \end{aligned} \quad (6.11)$$

where $M-1$ refers to the number of interferers concerned. Alternatively equation (6.11) can be rewritten as

$$SINR(M-1) = \frac{1}{1/a - 1} \quad (6.12)$$

where, $a = P_0^{-1} A_0^H R_{xx}^{-1} A_0$. Due to its simplicity, (6.11) will be used throughout this Chapter for analysis. However in real applications what we can obtain are $\hat{R}_{nn}$ and $\hat{R}_{xx}$, the estimation of R_{nn} and R_{xx} , respectively, where the expected value in (6.1) is replaced by a time average over a finite collection of data. For finite data collection, it is proven that (6.11) will give a better output *SINR* if $\hat{R}_{nn}$ is available [129]. In the simulation presented in this Chapter, only $\hat{R}_{xx}$ is used, because it is more easily applied.

It is of interest to know how the performance of the antenna changes, when an M -th interferer enters the system. It is noted that for a M -element antenna array, the DOA of the M -th interferer A_M can be expressed uniquely in the space spanned by vectors A_0 and A_i ($i=1,2,\dots,M-1$) if these vectors are independent of each other; that is

$$A_M = cA_0 + \sum_{i=1}^{M-1} d_i A_i \quad (6.13)$$

Since $R_{xx}^{-1}A_0$ is orthogonal to A_i ($i=1,2,\dots,M-1$), and $R_{xx}^{-1}A_i$ is orthogonal to A_0 and A_j ($j=1,2,\dots,M-1$, and $j \neq i$), after some calculation, we find

$$c = \frac{A_0^H R_{xx}^{-1} A_M}{A_0^H R_{xx}^{-1} A_0} = \frac{w_{opt}^H A_M}{w_{opt}^H A_0} \quad (6.14)$$

and $d_i = \frac{A_i^H R_{xx}^{-1} A_M}{A_i^H R_{xx}^{-1} A_i}$

where R_{xx} is given by (6.1) and w_{opt} is the optimum weighting vector given by (6.2) for the case of one desired user plus $M-1$ interferer users. It is noted that c is the correlation coefficient between w_{opt} and A_M normalized by the correlation coefficient between the w_{opt} and A_0 of the desired user. Equivalently, d_i is also the normalized coefficient if the i th interferer is treated as the desired user. Using (6.14), the equation (6.13) can be rewritten as

$$A_M = \frac{w_{opt}^H A_M}{w_{opt}^H A_0} A_0 + \sum_{i=1}^{M-1} \frac{A_i^H R_{xx}^{-1} A_M}{A_i^H R_{xx}^{-1} A_i} A_i \quad (6.15)$$

As mentioned earlier, an M -element array can reject $M-1$ interferers effectively. It is expected that if an M th interferer enters the system, the array performance will suffer some degradation. The amount of degradation mainly depends on the magnitude of c in (6.13). In a special case, if $c=0$, that is, A_M is orthogonal to A_0 and A_M is a linear combination of A_i ($i=1,2,\dots,M$), the antenna array can reject M th interferer completely. This indicates that the impact of M th interferer on the performance of antenna array depends on the DOA of

M th interferer. More results on how the output SINR of array is affected by the M th interferer is given in next section.

6.3. Derivation of the antenna performance for $M \leq N$

Compton [125] gave detailed analytical results where two interferences are incident on a 2-element array but did not consider a more general case. He found that the second interference signal had little effect if its INR was less than 10 dB ($SNR = 0$ dB and $INR = 20$ dB for first interference). As INR for the second interferer increases, the only way for the array to reduce the error signal is to turn off the weights.

The influence of diversity order and number of dominant interferers were also studied in [14] by simulation with $M=2,3,4$ and $N=0,1,2,3$ respectively. The results showed that the required SIR for given BER changed greatly with the number of M and N . For example, with 2-element array, the required input SIR (signal to interference ratio) is -5.9 dB for $N=1$, and 4.8 dB for $N=2$ to achieve $BER = 10^{-3}$. It is noticed that there is 10.7 dB degradation of SIR here.

In this section, we first derive the performance of the antenna array when N interferers impinge on the system. The performances of array under three special cases are discussed in detail. Simulation results are presented in the next section.

Suppose that there are N interferers ($N \geq M$) with the powers P_i ($i=1,2,\dots,N$) impinging on an M -element antenna array. The covariance matrix of received signal is

$$R = R_{xx} + \sum_{i=1}^N P_i A_i A_i^H \quad (6.16)$$

or in matrix form

$$R_{xx} + X P X^H \quad (6.17)$$

where, R_{xx} is defined in (6.1) and

$$X = [A_M \ A_{M+1} \ \dots \ A_N] \quad \text{and} \quad P = \begin{bmatrix} P_M & 0 & \dots & 0 \\ 0 & P_{M+1} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & P_N \end{bmatrix} \quad (6.18)$$

It is noted that, no matter how many interferers impinge on the array, the optimum weighting vector which minimizes the objective function $\langle |w^H X(n) - r(n)|^2 \rangle_N$ is of the form

$$w_{opt}(N) = R^{-1} A_0 \quad (6.19)$$

regardless the scale, where $r(n)$ is a reference signal. Again, using the results in (6.11), the SINR is

$$SINR(N)_1 = A_0^H R_1^{-1} A_0 \quad (6.20)$$

where

$$R_1 = R_{nn} + X P X^H \quad (6.21)$$

where R_{nn} was defined implicitly in (6.1). The subscript 1 in $SINR(N)_1$ is used to distinguish the formula derived later on. Using the matrix inversion lemma

$$B^{-1} = (A + X C X^H)^{-1} = A^{-1} - A^{-1} X (C^{-1} + X^H A^{-1} X)^{-1} X^H A^{-1} \quad (6.22)$$

we have

$$\begin{aligned} R_1^{-1} &= (R_{nn} + X P X^H)^{-1} = R_{nn}^{-1} - R_{nn}^{-1} X (P^{-1} + X^H R_{nn}^{-1} X)^{-1} X^H R_{nn}^{-1} \\ &= R_{nn}^{-1} - R_{nn}^{-1} X (P^{-1} + D)^{-1} X^H R_{nn}^{-1} \end{aligned} \quad (6.23)$$

where, D is a $(N-M+1) \times (N-M+1)$ matrix which is defined as

$$D = X R_{nn}^{-1} X^H =$$

$$\begin{aligned}
&= \begin{bmatrix} d_{MM} & d_{M(M+1)} & \cdots & d_{MN} \\ d_{(M+1)M} & d_{(M+1)(M+1)} & \cdots & d_{(M+1)N} \\ \cdots & \cdots & \cdots & \cdots \\ d_{NM} & d_{N(M+1)} & \cdots & d_{NN} \end{bmatrix} \\
&= \begin{bmatrix} A_M^H R_{nn}^{-1} A_M & A_M^H R_{nn}^{-1} A_{M+1} & \cdots & A_M^H R_{nn}^{-1} A_N \\ A_{M+1}^H R_{nn}^{-1} A_M & A_{M+1}^H R_{nn}^{-1} A_{M+1} & \cdots & A_{M+1}^H R_{nn}^{-1} A_N \\ \cdots & \cdots & \cdots & \cdots \\ A_N^H R_{nn}^{-1} A_M & A_N^H R_{nn}^{-1} A_{M+1} & \cdots & A_N^H R_{nn}^{-1} A_N \end{bmatrix}
\end{aligned} \tag{6.24}$$

Let

$$\begin{aligned}
e_i &= A_0^H R_{nn}^{-1} A_i = w_{opt}^H A_i \quad i = M, M+1, \dots, N \\
nd \quad e &= [e_M \ e_{M+1} \ \cdots \ e_N]
\end{aligned} \tag{6.25}$$

then

$$SINR(N)_1 = A_0^H R_1^{-1} A_0 = SINR(M-1) - e^H (P^{-1} + D)^{-1} e \tag{6.26}$$

Since $P^{-1} + D$ is a positive definite matrix, $SINR(N)_1$ is always less or equal to $SINR(M-1)$.

Based on the results in (6.26), the following three special cases are discussed.

Case 1: $N=M$. When $N=M$, (6.26) can be rewritten as

$$SINR(M) = SINR(M-1) - \frac{P_M \|e_M\|^2}{1 + P_M d_{MM}} \tag{6.27}$$

From the definition in (6.25), it is seen that e_M is the correlation coefficient between w_{opt} and A_M . Using the results of equation (6.15) and (6.25), d_{MM} can be rewritten as

$$d_{MM} = A_M^H R_{nn}^{-1} A_M = c^2 A_0^H R_{nn}^{-1} A_0 + \sum_{i=1}^{M-1} d_i^2 A_i^H R_{nn}^{-1} A_i \tag{6.28}$$

Equation (6.28) indicates that d_{MM} is related to the relative angular positions between A_M and $A_d, A_i (i=1,2,\dots,M-1)$ respectively as mentioned in section 2. If A_M orthogonal to w_{opt} (and A_d), then $SINR(M) = SINR(M-1)$, otherwise $SINR(M) < SINR(M-1)$.

Case 2: $N = N_D + N_W$, but N_D is less than M , where N_D is number of dominant interferers and N_W is number of weak interferers. When $N_D = M-1$ and $P_i \ll d_{ii} (i=M, M+1, \dots, N)$, we have

$$\begin{aligned} SINR(N)_1 &= SINR(M-1) - e \left(P^{-1} + D \right)^{-1} e^H \\ &= SINR(M-1) - e P e^H = SINR(M-1) - \sum_{i=M}^N P_i \|e_i\|^2 \end{aligned} \quad (6.29)$$

Equation (6.29) indicates that $SINR(N)$ is inversely related to the square of the correlation coefficient between w_{opt} and $A_i, (i = M, M+1, \dots, N)$. Equation (6.29) also suggests a simple way to simulate the system performance when there are a large number of weak interferers to be considered. We can first study the system performance $SINR(M-1)$ by considering the dominant interferers, and then approximate the $SINR(N)$ using (6.29). In order to distinguish the result in (6.26) from the result in (6.29), the notation

$$SINR(N)_2 = SINR(M-1) - \sum_{i=M}^N P_i \|e_i\|^2 \quad (6.30)$$

is used.

Case3: Treating the N_w weak interferences as noise. It is interesting to compare the results in (6.26) and (6.29) with the method used in literature which lump a number of weak interferers into an equivalent Gaussian noise. If the weak interferences are treated as noise, the matrix in (6.21) can be modified as

$$R_2 = R_{nn} + \rho^2 I \quad (6.31)$$

where $\rho^2 = \sum_{i=M}^N P_i$ and assuming that DOAs of users A_i ($i=M, M+1, \dots, N$) are normalized vectors. The *SINR* is

$$SINR(N)_3 = A_0^H R_2^{-1} A_0 = A_0^H (R_{nn} + \rho^2 I)^{-1} A_0 \quad (6.32)$$

Since R_{nn} is related to dominant interferers, without loss of the generality, assuming

$\|R_{nn}^{-1} \rho^2\| \ll 1$, then

$$\begin{aligned} SINR(N)_3 &= SINR(M-1) - \rho^2 A_0^H R_{nn}^{-1} R_{nn}^{-1} A_0 \\ &= SINR(M-1) - A_0^H R_{nn}^{-1} (\rho^2 I) R_{nn}^{-1} A_0 \end{aligned} \quad (6.33)$$

It is noticed that (6.29) can also be rewritten as

$$SINR(N)_2 = SINR(M-1) - A_0^H R_{nn}^{-1} \left(\sum_{i=M+1}^N P_i A_i A_i^H \right) R_{nn}^{-1} A_0 \quad (6.34)$$

Since $\sum_{i=M}^N P_i A_i A_i^H$ is a non-negative matrix, we have

$$\left\| \sum_{i=M}^N P_i A_i A_i^H \right\| \leq \sum_{i=M}^N P_i \|A_i A_i^H\| = \sum_{i=M}^N P_i = \rho^2 \quad (6.35)$$

Hence *SINR* in equation (6.29) is equal to or larger than *SINR* in equation (6.33). As expected equation (6.33) gives the performance of the worst scenario. The remaining problem is whether the treatment of weak interferers as noise is valid in real life applications. This question is answered by the simulation results presented in next section. Furthermore, the comparisons among the performances in (6.26), (6.29) and (6.33) are also made.

6.4 Simulation results

In a simulation experiment, a cellular system using a modified TDMA transmission format is considered. Up to six first tier interferers and up to twelve second tier interferers

contribute to the interference. Moreover each co-channel user at least has some frequency offset with other users [127]. An M -element circular array is used. We also assumed that all the interferers are located at the boundaries of their respective cells and are closest to the desired cell.

Figure 6.1 and 6.2 show the results for both non-fading and fading cases with $M=2,4,6$ and dominant interferers $N=1,2,\dots,6$ respectively. The results are obtained by averaging over 1000 simulation runs. In case of "Formula, non-fading", the average power of each user is used according to its position to base station and the fourth power law. DOAs of users are randomly chosen. The results are calculated directly from equation (6.26). In case of "Simulation, non-fading, DMI", the DMI algorithm is used to estimate the optimum weighting vector by simulating the real cellular system scenarios. The powers of users are calculated according to the propagation loss due to distance only and $SINR$ is obtained from the transmitting data sequence. In case of "Simulation, fading 1/48000 (simplified as 1/4.8k later on), DMI", the Rayleigh channel model at normalized fading rate 1/4.8k is used for each user. As we expected that the $SINR$ decreased with an increase in the number of interferers. It is also noted that the performance of the antenna array is sensitive to input SNR which is defined at each antenna element. We see that when N equals M and input SNR is 40 dB, the performance has a significant degradation compared to the performance when $N=M-1$. However, in case of input $SNR=20$ dB, output $SINR$ changes smoothly with an increase in the number of interferers. The major reasons of large degradation in the performance for an input $SNR=40$ dB are: (i) in case of $N \geq M$, the array doesn't have enough degrees of freedom to reject the interference effectively; (ii), the dominant factor that affects the performance is the interference level relative to noise. For low SNR , INR is also small, and the system is unable to identify and reject the interference as effectively as for high SNR .

Since blind adaptation is very useful in some applications, Figure 6.3 and 6.4 show the performance comparisons between DMI [24] and blind PHASE [127] defined in Chapter 4 for input $SNR = 20, 40$ dB respectively. It is expected that DMI with a training sequence would give better performance. This is borne out by the results when $M>N$. However when

Figure 6.1 Comparison of performances of adaptive antenna array with different number of antenna elements and users. SNR = 20 dB.

Figure 6.2. Comparison of performances of adaptive antenna array with different number of antenna elements and users. SNR = 40 dB

Figure 6.3. Comparison of performances of DMI and PHASE. SNR = 20 dB

Figure 6.4 Comparison of performance of DMI and PHASE. SNR = 40 dB

$M < N$ the difference between DMI and PHASE algorithms is not significant. Generally fast convergence is a great motivation to use DMI or its modified version, but when it is impossible to transmit the training sequence or overhead due to it is prohibitive, the blind algorithm is preferred.

We have shown in section 6.3 that treating weak interferences from the second tier as noise gives the most pessimistic results. Simulation examples are presented here to corroborate this conclusion. Following scenarios are compared:

- (1) Treat the weak interferers using (6.26) (case 1)
- (2) Treat the weak interferers using the approximation (6.29) (case 2)
- (3) Treat the weak interferers as additive Gaussian white noise (6.33) (case 3)

Figure 6.5, 6/6, and 6/7 present the results for comparison of the system performances in above three scenarios, where,

N_1 is the number of dominant interferers from the first tier. The average power of each interferer is -19 dB.

N_2 is the number of weak interferers at the second tier. The average power of each interferer is -24 dB ($cn_2=1/16$), -31 dB ($cn_2=1/36$) respectively.

M is the number of antenna elements.

For each scenario, the dashed lines present the results calculated from the formula in equations (6.26), (6.29) and (6.33) respectively. In this case, only the DOA and average power of each user are used. The solid lines indicate the simulation results. In this case, the Rayleigh channel at the normalized fading rate $1/4.8k$ is used for each user. The simulation results are based on averaging 1000 simulation runs. It is expected that results calculated from the formula are better than that from the simulation runs using the real data sequence, since the formula assumed no cross-correlation between the users. Results showed that situation (3) gives the worst performance in all cases and situation (1) gives the best performance. The higher SNR and INR , the bigger the difference of the $SINR$ between (1) and (3). It noted that the differences between (1) and (3) increases with the increase in the number of weak interferers. The results also indicate that pessimistic results are

obtained from lumping the weak interferences with the Gaussian noise.

The Figure 6.5, 6.6, and 6.7 also present some approximate results giving better performance in situation (2) than that for the situation (3). When input SNR is 30 and 20 dB, and the average power of weak interferers is -31 dB ($cn^2=1/36$), the approximate method provides performance very close to that of the real situations (1).

6.5 The Transition Performance of Antenna Array with Impinging of New Interference

In Section 6.4, we demonstrated the steady state SINRs of antenna array when a number of interfering users impinge on array. In this section, we will show the transition process of SINR when a new interfering user is impinging on array. The simulation parameters are shown in Table 6.1, where -19 dB is a average relative power of interferer from first tier at the boundary of co-channel cell for TDMA system with $k=3$. Both the

Table 6.1: Parameters for Figure 6.8 with desired user's DOA 50 degree and relative power 0 dB. $SNR=20$ dB

			Interfering users			
			#1	#2	#3	#4
Relative power(dB)			-19	-19	-19	-19
Case a:	DOA		165°	135°	200°	300°
	when entering system		n=0	n=0	n=200	n=400
	SINR (dB)	(6.27)	25.6988		21.3370	21.2225
		Simulation	25.5709		20.8962	20.8348
Case b:	DOA		300°	165°	135°	200°
	when entering system		n=0	n=0	n=200	n=400
	SINR (dB)	(6.27)	25.6227		25.6149	21.2225
		Simulation	25.4721		25.4875	21.3106

Figure 6.5 Comparison of output SINRs of antenna array with a larger number of interfering users. Solid line --- results from simulation Dashed line --- results from the formula. SNR = 20 dB

Figure 6.6 Comparison of output SINRs of antenna array with a larger number of interfering users. Solid line --- results from simulation
Dashed line --- results from the formula. SNR = 30 dB.

Figure 6.7 Comparison of output SINRs of antenna array with a larger number of interfering users. Solid line --- results from simulation Dashed line --- results from the formula . SNR = 40 dB.

Table 6.1: Parameters for Figure 6.8 with desired user's DOA 50 degree and relative power 0 dB. SNR=20 dB

			Interfering users			
			#1	#2	#3	#4
Relative power(dB)			-19	-19	-19	-19
Case c:	DOA		200	165	135	300
	when entering system		n=0	n=0	n=200	n=400
	SINR (dB)	(6.27)	21.4462		21.3370	21.2225
		Simulation	21.3106		21.2438	21.0571
Case d:	DOA		165	135	200	300
	when entering system		n=0	n=0	n=0	n=0
	SINR (dB)	(6.27)	21.2225			
		Simulation	21.0330			

results from the simulation of PHAE algorithm and calculated from formula (6.27) are also presented in Table 6.1 for comparison.

Figure 6.8 shows that the steady state SINRs of array is almost same regardless the order of appearance of interfering users and the PHASE algorithm provides the very close performance as DMI algorithm does. It is noted that the drop of SINR due to the appearance of a new interfering user greatly depends on the correlation coefficient (CC) between desired user and interfering user. which is defined as

$$\rho = \frac{|A_d^H A_i|}{\sqrt{A_d^H A_d A_i^H A_i}} \quad (6.36)$$

and $A_d^H A_d = A_i^H A_i = M$. The larger the CC, the bigger the drop of the performance. This result is consistent with the analytical result in equation (4.37) and Section 6.2. In order to demonstrate this property of array, let's consider a simple example in which only desired user and single interferer is involved. The SINRs of array due to interferer impinging on the

Figure 6.8 The transition processes of SINR of array with new interferer impinging on arra. Dashed line --- DMI. Solid line --- PHASE. Simulation parameters are presented in Table 6.1.

array with different DOAs are shown in Table 6.2. where -32 dB is a average relative power of interferer from the second tier at the boundary of co-channel cell for TDMA system with $k=3$.

Table 6. 2: SINR of array with different DOAs of interferers for desired user with power 0 dB and DOA at 50°. SNR=20 dB

		Interferers			
		#1	#2	#3	#4
DOA		135	165	300	200
CC between desired user and interferer		.0008	.03250	-.2393	-.8542
Case 1:	Relative power (dB)	-19	-19	-19	-19
	SINR (dB)	26.0206	26.0168	25.8087	21.9669
Case 2:	Relative power (dB)	0	0	0	0
	SINR (dB)	26.0206	26.0160	25.7652	20.3689

where, SINR, using results in (4.11), is calculated by

$$SINR = MSNR \left(\frac{\sigma^2 + MP_i(1 - \rho^2)}{\sigma^2 + MP_i} \right) \quad (6.37)$$

and P_i is the power of interferer. Ideally, output SINR of M -element array is $M \cdot SNR$, where M is called the processing gain of array. The results in Table 6.2 indicate that DOA of interferer affects the SINR of array significantly. And the SINR of array is more sensitive to DOA of interferer than to the power level of interferer. For instance, the output SINR doesn't change and is equal to $M \cdot SNR$ whether the power of interferer #1 is -19 dB or 0 dB. However, when interferer #4 is impinging on array, the SINR drops by 4 dB from $M \cdot SNR$. Even when the power of the interfering user increases 19 dB from -19 dB, there is only 5.6 dB drop from $M \cdot SNR$. The statement is also corroborated by the simulation results shown in Figure 6.9, where the transition SINR of array due to the coming of an dominant or

interfering user is presented. The parameters for simulation is shown in Table 6.3. It is demonstrated in Figure 6.9, the big drop of SINR comes with the appearance of an interferer with DOA equal to 200 degree ($\rho = .8542$) whether its power is -19 dB or -32 dB. For interferer with DOA equal to 300 degree ($\rho = .03250$), there is a minor change of SINR whether its power is -19 dB or -32 dB.

Table 6.3: Parameters for Figure 6.9 with desired user's DOA at 50 degree and relative power 0 dB. (SNR=20 dB)

		Interfering users			
		#1	#2	#3	#4
Case a:	DOA	165°	135°	200°	300°
	Relative power(dB)	-19	-19	-19	-32
	when entering system	n=0	n=0	n=200	n=400
Case b:	DOA	165°	135°	300°	200°
	Relative power(dB)	-19	-19	-32	-19
	when entering system	n=0	n=0	n=200	n=400
Case c:	DOA	165°	135°	200°	300°
	Relative power(dB)	-19	-19	-32	-19
	when entering system	n=0	n=0	n=200	n=400
Case d:	DOA	165°	135°	300°	200°
	Relative power(dB)	-19	-19	-19	-32
	when entering system	n=0	n=0	n=200	n=400

6.6 Summary

The performance of channel diversity with the number of interfering signals is presented in this Chapter. The output SINR suffers a big drop when $N=M$ and input SNR is high (Figures 6.2 and 6.4). The performance degrades linearly with the increase of number of interferers when $N>M$ and SNR is moderate. For specific environment (Figures 6.1 and

Figure 6.9 The transition process of SINR of array due to the order of dominant and weak interferer. Dashed line --- DMI. Solid line --- PHASE. Simulation parameters are presented in Table 6.3.

6.3), the performance degradation due to a newly added user depends on the angular position of DOA of the new user in the space spanned by the DOAs of existing users in array. The results also demonstrates that it is too pessimistic to treat the interference from the second tier as the noise, specially when the number of weak interference is large or the input SNR is high (Figures 6.5, 6.6 and 6.7). It is noted from Figure 6.8 and 6.9 that the output SINR of array is more sensitive to the DOA of interferer than the power of interferer. Finally, the blind PHASE algorithm can provide a performance close to that of DMI in some cases (Figures 6.3, 6.4, 6.8 and 6.9). In practical applications, a trade off between the DMI and PHASE algorithms can be expected.

Chapter 7 Conclusions

7.1 Thesis Summary

This thesis presented a comprehensive study of the performance of modified TDMA with the cyclostationary signal processing and adaptive antenna array. The blind algorithms are proposed to reject the co-channel interference, improve the spectrum efficiency and system capacity for future indoor cellular systems. Furthermore, the algorithms help us to understand the behavior of cyclostationary signal processing better for finite data collection,

-- Two new algorithms M-SCORE in Section 4.2 and PHASE in Section 4.4 have been proposed for blind adaptive extraction of a signal in the presence of interference by cyclostationary signal processing using an antenna array. The algorithms operate in an interference-limited system in which the desired and interfering signals have equal symbol rates, but slightly different carrier frequencies. Work demonstrated that based on the cyclostationarity of the frequency offset between co-channel users, the antenna array can quickly distinguish one user from another.

-- Based on finite data collection, the specific solution for the optimum weight vector of M-SCORE is derived in Section 4.3.2 for the case of one user and single interference, which also provides some insights on how the performance changes with the number of samples N , the cyclic-correlation and the correlation coefficient (CC) between the DOA of user and interference. Furthermore, the simulation results demonstrate that, if N is finite, the M-SCORE can provide better results than those of Auto-SCORE.

-- In Section 4.4.4, a two-node algorithm which combines PHASE algorithm with DMI algorithm is proposed. It is shown that not only the speed of convergence but also the SINR can be improved significantly with PHASE algorithm to start up blindly and DMI algorithm to take over after some point based on the estimated data.

-- Due to three type of factors: doppler frequency shift, estimation error and frequency generator error, it is impossible to know the exact α in practice when the cyclic-correlation

function of received data is calculated. In turn, these three factors will influence the system performance. The robustness of existing and proposed algorithms to the perturbation of cyclostationarity and the behavior of antenna array in presence of a large number of interfering users are studied in this thesis. Simulation results provided some insight on how much error the system can tolerate for the given time period and frequency offsets.

-- Compared to the existing blind algorithms which also exploit the cyclostationarity of received signal, the PHASE algorithm provides a simpler and faster converging means to estimate the channel phase for diversity combining as shown in Section 5.6. Analytical and simulation results for the PHASE algorithm are presented and performances are compared with DMI (direct matrix inversion), and existing blind algorithms. Based on the PHASE algorithm, a TDMA system with the new channel assignment scheme called Cyclic-TDMA (CTDMA) is proposed in Section 5.7. The simulation results also show that the proposed PHASE algorithm is relatively simple and very promising in applications to indoor wireless communication where interference rejection and increased spectrum efficiency are the objectives. Simulation results are presented to confirm interference rejection capabilities.

-- The comparison between sectored antenna with adaptive antenna is made in Section 5.8. It demonstrated that adaptive array will provide the better SINR than does sectored array in flat fading case. It is because that adaptive array can change its null directions according to the DOAs of interfering users, while performance of sectored array mainly depends on the communication environment.

-- In Chapter 6, the thesis presented analytical and simulation results on the output SINR of an antenna array for M elements and N interfering users in digital cellular system scenarios, including the case where $N=M$ and $N>M$. The analytical expressions are given for following three cases: i) $M=N$; ii) $M<N$; and iii) a larger number of weak interfering users are involved. It proved that by lumping a number of weak interfering users into Gaussian noise gives the worst SINR performance. In case of iii), a new approximating approach is proposed for the simplicity of analysis and simulation. the Simulation demonstrated that proposed approximating method present fairly close performance to the

real scenarios in certain cases. Simulation also showed that, in practice, the output SINR (Signal to interference plus noise ratio) of the antenna array decreases with the increase of N for fixed M even if $N < M$. There is a big drop of output SINR as N goes from $M-1$ to M for high input SNR (Signal to noise ratio), for example $\text{SNR}=40$ dB. However, if input SNR is low, for example 20 dB, there is no significant change of SINR with increase of N .

7.2 Suggestions for Future Work

Following questions are of interest and important for further research.

-- Robustness of blind algorithm

Although a performance evaluation under the perturbation of baseband carrier frequency offset has been conducted in this thesis, there is no mention of how the robustness of the proposed blind algorithm can be increased for such a perturbation. It is desirable to find some possible remedies to the problem.

-- Blind Algorithm for Multipath Scenario

The main focus of this thesis is on how to reject the co-channel interference blindly. However, the proposed blind algorithms can only be used for flat fading channel in principle and can not be used to reduce the ISI effectively. For large time delay spread, blind equalization and estimation algorithm is needed. Although there are several algorithms have been published about blind equalization [97,98,110-115], there is only ISI and Gaussian noise but interference to be considered in these researches. It is desirable to develop a blind algorithm which can jointly optimize both the rejection of co-channel interference by PHASE algorithm and ISI by blind equalization technics.

-- Comparison between Sector Antenna with Adaptive Antenna

This thesis analyzed the performance of adaptive antenna array in micro-cellular communication environment. Recently there has been a considerable interest in using sector antenna array or combination of sector and adaptive antenna array for future cellular systems [79,119]. It is of interest to compare the performance between adaptive and sector antenna array in terms of the implementation complexity, ability to reject interference and reduce time delay spread under different traffic and channel models. Some comparison has

been made in Section 5.8 for flat fading channel, but since the performance of the sector array greatly depends on the surrounding geometry, further comparison should be made based on field trial measurement or ray tracing techniques to characterize the special communication environment in order to make a fair comparison.

-- BER and Outage Probability of Optimum Combining

In this thesis, the SINR of antenna array is investigated if a large number of interfering users are involved. However, in application, it is of also important to know the outage probability of system or BEP (bit error probability). The analytical expression of BEP for $M > N$ was derived for the zero-forcing adaptive array, which completely cancels the N interferers [126]. Since the array cannot completely cancel more than $M-1$ interferers, a zero-forcing result does not exist for $M < N$. However, for $M > N$ as well for $M < N$, the best (approximately) array weighting (in terms of minimizing the BER) is minimum MSE combining. This does substantially better than zero-forcing for $M > N$. However, there are no analytical results for MSE combining if more than one interferer are considered, only BER bounds for all cases of M and N are available [132]. The importance of analytical work of BEP for optimum combining is that we can quick calculate the performance of optimum combining for given any number M and N comparing the amount of time required for simulation.

-- Capacity of indoor cellular system with blind algorithm

It is observed that the proposed blind algorithm in this thesis uses a small portion bandwidth of channel to create the different cyclostationarities among co-channel users, by which the system can effectively reject the cochannel interference and improve the spectrum efficiency. It is of interest in comparing the spectrum efficiency (or system capacity) of a blind algorithm with the DMI algorithm, in which the training sequence is used for adaptation. Specifically, it is important to know which algorithm will give better performance for given system capacity (or BEP), traffic load, channel models, spectrum efficiency, converging time, complexity.

7.3 Comments on CAB algorithms

Since CAB algorithms have come to author's attention recently, no comparison study has been done among CAB algorithms and algorithms proposed in this thesis. However, following comments can be made based on [134 - 136].

-- CAB algorithm is an estimator of DOA of desired user and can be treated as a variation of maximal ratio combining, which means it can not be used as CCI cancellation method. Therefore there is no comparison between CAB and M-SCORE algorithms (see Chapter 4.2).

-- In case of co-channel interference, C-CAB or R-CAB algorithms must be used. They are equivalent to DMI algorithm when the data collect time is long enough. Furthermore, Mathematically, both C-CAB and M-SCORE algorithm are the same, although they are driven based on different objective functions. It is expected that C-CAB will give the same performance as M-SCORE does.

-- Simulation results showed C-CAB (or R-CAB) algorithms provide better performance than that the SCORE algorithm based on bit/ baud rate recovery but give the same performance as SCORE based on carrier recovery. Since we are only interested in the method based on carrier recovery and our simulation demonstrated that PHASE algorithm gives the better performance than SCORE algorithm for finite data collection, it is expected that PHASE algorithm will provides the better performance than C-CAB (R-CAB) algorithm.

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Appendix A. Derivation of eigenvalues and eigenvectors

In this Appendix, the eigenvalues and eigenvectors of a matrix are derived for one user and one interference environment. Suppose the matrix is generally given by

$$R = [A_1 \ A_2] \begin{bmatrix} k_1 & k_2 \\ k_3 & k_4 \end{bmatrix} \begin{bmatrix} A_1^H \\ A_2^H \end{bmatrix} \quad (\text{A.1})$$

where k_1, k_2, k_3 , and k_4 are any real numbers. A_1 and A_2 are the directional vectors of user and interference respectively. Suppose matrix R has eigenvalues λ_1 and λ_2 , and eigenvectors e_1 and e_2 , as we know that the eigenvectors of this matrix may be found by noting that two of the eigenvectors must lie in the plane spanned by A_1 and A_2 . These two eigenvalues must have the form

$$e = \alpha \times A_1 + \beta \times A_2 \quad (\text{A.2})$$

where α and β are constants to be determined by the requirement that

$$R \times e = \lambda e \quad (\text{A.3})$$

where λ is the corresponding eigenvalue. The constants α and β may be found by evaluating $R \times e$ from equation (A.1),

$$R \times (\alpha A_1 + \beta A_2) = \alpha A_1 (Mk_1 + Md k_2) + \frac{\alpha}{\beta} \beta A_2 (Mk_3 + Md k_4) + \frac{\beta}{\alpha} \alpha A_1 (k_1 Md + k_2 M) + \beta A_2 (k_3 Md + k_4 M) \quad (\text{A.4})$$

where $A_1^H A_1 = A_2^H A_2 = M$, and $A_1^H A_2 = A_2^H A_1 = d/M$. Let $y = \beta / \alpha$. The vector e will be an eigenvector if α and β are chosen so that

$$k_1 + dk_2 + ydk_1 + yk_2 = dk_3 + k_4 + \frac{k_3}{y} + d\frac{k_4}{y} \quad (\text{A.5})$$

The above equation then can be transferred into a quadratic equation, and we find

$$y^2 + by + c = 0, \quad (\text{A.6})$$

where $b = (k_1 + d^*k_2 - d^*k_3 - k_4)/(d^*k_1 + k_2)$, and $c = -(k_3 + d^*k_4)/(d^*k_1 + k_2)$. This quadratic equation has the two solutions

$$y_{1,2} = \frac{-b \pm \sqrt{b^2 - 4c}}{2} \quad (\text{A.7})$$

So that the two eigenvectors of matrix (A.1) are given by

$$e_1 = A_1 + y_1 A_2 \quad \text{and} \quad e_2 = A_1 + y_2 A_2 \quad (\text{A.8})$$

Specially, if $k_2 = k_3 = 0$, then the two solutions become

$$y_1 = \frac{a_1 + b_1}{2k_1 d} \quad (\text{A.9})$$

and

$$y_2 = \frac{a_1 - b_1}{2k_1 d} \quad (\text{A.10})$$

where

$$a_1 = k_4 - k_1 \quad (\text{A.11})$$

and

$$b_1 = \sqrt{a_1^2 + 4k_1 k_4 d^2} \quad (\text{A.12})$$

(A.10), (A.11), and (A.12) are the results shown in [122].

Appendix B. Matrix Inverse Relationships

Suppose R_{ss} represents a $M \times M$ covariance matrix with user only, R_{nn} represents a $M \times M$ covariance matrix with interference only, and both of them are given by

$$R_{ss} = P_1 A_1 A_1^H + \sigma^2 I \quad \text{and} \quad R_{nn} = P_2 A_2 A_2^H + \sigma^2 I \quad (\text{B.1})$$

respectively. Where, P_1 , P_2 and σ^2 are the powers of user, interference, and noise respectively. A_1 and A_2 are the directional arrival vectors of the user and interference respectively. Then the inverse matrix of R_{ss} and R_{nn} is given by

$$R_{ss}^{-1} = \frac{1}{\sigma^2} I - \frac{P_1 A_1 A_1^H}{\sigma^2 (\sigma^2 + MP_1)} \quad \text{and} \quad R_{nn}^{-1} = \frac{1}{\sigma^2} I - \frac{P_2 A_2 A_2^H}{\sigma^2 (\sigma^2 + MP_2)} \quad (\text{B.2})$$

If R_{xx} represents the covariance matrix with one user and interference, then it is of form

$$R_{xx} = P_1 A_1 A_1^H + P_2 A_2 A_2^H + \sigma^2 I = R_{ss} + P_2 A_2 A_2^H = R_{nn} + P_1 A_1 A_1^H \quad (\text{B.3})$$

Using the matrix inverse lemma, we have

$$R_{xx}^{-1} = R_{ss}^{-1} - \frac{P_2 R_{ss}^{-1} A_2 A_2^H R_{ss}^{-1}}{1 + P_2 A_2^H R_{ss}^{-1} A_2} \quad (\text{B.4})$$

and

$$R_{xx}^{-1} = R_{nn}^{-1} - \frac{P_1 R_{nn}^{-1} A_1 A_1^H R_{nn}^{-1}}{1 + P_1 A_1^H R_{nn}^{-1} A_1} \quad (\text{B.5})$$

After some calculation, we have that

$$R_{ss}^{-1} A_2 A_2^H R_{ss}^{-1} = \frac{1}{\sigma^2} \left(\frac{M^2 P_1^2 d^2 A_1 A_1^H}{\sigma^2 (\sigma^2 + MP_1)^2} - \frac{MP_1 d A_2 A_1^H}{(\sigma^2 + MP_1)} - \frac{MP_1 d A_1 A_2^H}{(\sigma^2 + MP_1)} + \frac{A_2 A_2^H}{\sigma^2} \right) \quad (\text{B.6})$$

Let

$$k = \frac{1}{1 + Ma} \left(1 + P_2 A_2^H R_{ss}^{-1} A_2 \right) = \frac{1}{1 + Ma} \left(1 + \frac{P_2}{\sigma^2} \left(M - \frac{M^2 d^2 P_1}{(\sigma^2 + MP_1)} \right) \right) \quad (\text{B.7})$$

where $A_1^H A_2 = A_2^H A_1 = Md$ and $A_1^H A_1 = A_2^H A_2 = M$. Let

$$SNR = a = \frac{P_1}{\sigma^2}; \quad INR = b = \frac{P_2}{\sigma^2} \quad (B.8)$$

Then the above equations can be simplified as

$$k = 1 + Ma + Mb + M^2 ab - M^2 abd^2 \quad (B.9)$$

and

$$R_{xx}^{-1} = k_1 A_1 A_1^H + k_2 A_1 A_2^H + k_3 A_2 A_1^H + k_4 A_2 A_2^H + \frac{1}{\sigma^2} I \quad (B.10)$$

where,

$$\begin{aligned} k_1 &= \frac{a(1+Mb)}{\sigma^2 k}; & k_2 &= \frac{Mab d}{\sigma^2 k} \\ k_3 &= \frac{Mabd}{\sigma^2 k}; & k_4 &= \frac{b(1+Ma)}{\sigma^2 k} \end{aligned} \quad (B.11)$$

Now suppose we have a matrix given by

$$R_{xx}^\alpha = R_{11}^\alpha A_1 A_1^H + R_{22}^\alpha A_2 A_2^H + R_{nn}^\alpha I \quad (B.12)$$

then, after some calculation, the equation (B.11) can be expressed as

$$\begin{aligned} R_{xx}^{-1} R_{xx}^\alpha &= \frac{(a_1 - c_1 a)(1+Mb)}{k} A_1 A_1^H + \frac{Mda(c_1 b - b_1)}{k} A_1 A_2^H \\ &+ \frac{Mdb(c_1 a - a_1)}{k} A_2 A_1^H + \frac{(b_1 - c_1 b)(1+Ma)}{k} A_2 A_2^H + c_1 I; \end{aligned} \quad (B.13)$$

where,

$$S^\alpha NR = a_1 = \frac{R_{ss}^\alpha}{\sigma^2}; \quad I^\alpha NR = b_1 = \frac{R_{ii}^\alpha}{\sigma^2}; \quad N^\alpha NR = c_1 = \frac{R_{nn}^\alpha}{\sigma^2} \quad (B.14)$$

Appendix C: The Correlation among the eigenvectors

Suppose a matrix R is a $M \times M$ covariance matrix with appearance of one desired signal and one interference and is given by

$$R_{xx} = P_0 \mathbf{A}_0 \mathbf{A}_0^H + P_1 \mathbf{A}_1 \mathbf{A}_1^H + \sigma^2 \mathbf{I} \quad (\text{C.1})$$

where P_0 and P_1 are constants related to signal and noise powers respectively. They could be real or complex numbers. Let $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_M$ denote R_{xx} 's eigenvalues. Then the M eigenvalues of R_{xx} are given by

$$\lambda_k = \begin{cases} \mu_k + \sigma^2 & k = 1, 2 \\ \sigma^2 & k = 3, \dots, M \end{cases} \quad (\text{C.2})$$

and also let $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_M$ represent their associated eigenvectors. Where,

$$\mu_1 + \mu_2 = M(P_s + P_i) \text{ and } \mu_1 \mu_2 = M^2 P_s P_i (1 - d^2) \quad (d = \mathbf{A}_d^H \mathbf{A}_i / M = \mathbf{A}_i^H \mathbf{A}_d / M). \text{ Then}$$

$$R_{xx} = \sum_{k=1}^M \lambda_k \mathbf{v}_k \mathbf{v}_k^H = \mathbf{Y} \Sigma \mathbf{Y}^H \quad (\text{C.3})$$

where

$$\mathbf{Y} = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_M], \quad (\text{C.4})$$

$$\mathbf{Y}^H \mathbf{Y} = \mathbf{I}_M$$

and

$$\Sigma = \begin{bmatrix} \mu_1 + \sigma^2 & 0 & \dots & 0 & 0 \\ 0 & \mu_2 + \sigma^2 & \dots & 0 & 0 \\ \dots & \dots & \dots & 0 & 0 \\ 0 & 0 & 0 & \sigma^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma^2 \end{bmatrix}, \quad (\text{C.5})$$

Moreover, for any $k > 2$, from equation (C.2)

$$R \mathbf{v}_i = \lambda \mathbf{v}_i = \sigma^2 \mathbf{v}_i \quad (\text{C.6})$$

But

$$R \mathbf{v}_i = (P_d \mathbf{A}_d \mathbf{A}_d^H + P_i \mathbf{A}_i \mathbf{A}_i^H + \sigma^2 \mathbf{I}) \mathbf{v}_i = \sigma^2 \mathbf{v}_i \quad (\text{C.7})$$

and together they imply

$$\left(P_d \mathbf{A}_d \mathbf{A}_d^H + P_i \mathbf{A}_i \mathbf{A}_i^H \right) \mathbf{v}_i = 0 \quad (\text{C.8})$$

or

$$\mathbf{A}_d^H \mathbf{v}_i = 0 \quad \text{and} \quad \mathbf{A}_i^H \mathbf{v}_i = 0 \quad i > 2 \quad (\text{C.9})$$

since $P_d \mathbf{A}_d \mathbf{A}_d^H + P_i \mathbf{A}_i \mathbf{A}_i^H$ and $\mathbf{v}_i (i > 2)$ don't equal to zero generally [121].

It is shown that the eigenvectors $\mathbf{v}_1$ and $\mathbf{v}_2$ are located in the space spanned by the vectors $\mathbf{A}_d$ and $\mathbf{A}_i$, that is $\mathbf{v}_1$ and $\mathbf{v}_2$ are the linear combination of $\mathbf{A}_d$ and $\mathbf{A}_i$ respectively. Although the results are proved for symmetric matrix, the conclusion can be generalized to a non-symmetric matrix.

If we define the subspaces spanned by $[\mathbf{v}_1, \mathbf{v}_2]$ and $[\mathbf{v}_3, \dots, \mathbf{v}_M]$ as the signal-plus-interference subspace and noise subspace respectively, the covariance matrix in (C.1) may be rewritten as in [125]

$$\mathbf{R} = \mathbf{V}_s \Sigma_s \mathbf{V}_s^H + \mathbf{V}_n \Sigma_n \mathbf{V}_n^H \quad (\text{C.10})$$

where $\mathbf{V}_s = [\mathbf{v}_1, \mathbf{v}_2]$, $\mathbf{V}_n = [\mathbf{v}_3, \dots, \mathbf{v}_M]$, $\Sigma_s = \text{diag}[\lambda_1, \lambda_2]$, and $\Sigma_n = \text{diag}[\lambda_3, \dots, \lambda_M]$. It is noted that $\mathbf{V}_s$ orthogonal to $\mathbf{V}_n$.

Suppose, the directional arrival of user $\mathbf{A}_d$ is known exactly, the optimum weight is given by

$$\mathbf{w}_{opt} = \mathbf{R}^{-1} \mathbf{A}_d = \left[\mathbf{V}_s \Sigma_s^{-1} \mathbf{V}_s^H + \mathbf{V}_n \Sigma_n^{-1} \mathbf{V}_n^H \right] \mathbf{A}_d = \mathbf{w}_s + \mathbf{w}_n = \mathbf{w}_s \quad (\text{C.11})$$

The covariance matrix over finite time can be written as

$$\hat{\mathbf{R}} = \hat{\mathbf{V}}_s \hat{\Sigma}_s \hat{\mathbf{V}}_s^H + \hat{\mathbf{V}}_n \hat{\Sigma}_n \hat{\mathbf{V}}_n^H \quad (\text{C.12})$$

and the estimate optimum weight is given

$$\hat{\mathbf{w}}_{opt} = \hat{\mathbf{R}}^{-1} \mathbf{A}_d = \left[\hat{\mathbf{V}}_s \hat{\Sigma}_s^{-1} \hat{\mathbf{V}}_s^H + \hat{\mathbf{V}}_n \hat{\Sigma}_n^{-1} \hat{\mathbf{V}}_n^H \right] \mathbf{A}_d = \hat{\mathbf{w}}_s + \hat{\mathbf{w}}_n \quad (\text{C.13})$$

In this case $\hat{\mathbf{w}}_n \neq 0$ in general for the covariance matrix over finite data samples.

Appendix D. Derivation of PHASE algorithm

Suppose only two users to be considered, $X_1(n)$ and $X_2(n)$ are the received data sequences for desired signal and interference, and the signal power and interference power equal to 1. With the same expression defined in equation (4.4), the received signal vector can be written as

$$X(n) = \begin{bmatrix} X_1(n) \\ X_2(n) \end{bmatrix} = s_0(n)A_0 + s_1(n)A_1 + n(n) \quad (D.1)$$

where,

$$\begin{aligned} A_i &= \begin{bmatrix} e^{j\theta_{1i}} & e^{j\theta_{2i}} \end{bmatrix}^T \quad i = 0, 1 \\ s_i(n) &= d_i(n) \sin 2\pi f_i n \quad i = 0, 1 \\ n(n) &= \begin{bmatrix} n_1(n) & n_2(n) \end{bmatrix}^T \end{aligned} \quad (D.2)$$

A_i is DOA of user i , $f_i(i=1,2)$ is baseband carrier frequency. Let

$$r_1(n) = X_1(n) e^{-j2\pi 2f_1 n} \quad (D.3)$$

be the reference signal, then, the cross cyclic-correlation between (D.1) and (D.3) can be rewritten as

$$R_1^{2f_1} = \langle X(n) r_1^*(n) \rangle_N = \begin{bmatrix} R_{11}^{2f_1} & R_{21}^{2f_1} \end{bmatrix}^T \quad (D.4)$$

where, assuming $\langle s_i(n)s_i^*(n) \rangle_N = 1, (i=1,2)$, the cyclic-correlation expressions in detail are given by

$$\begin{aligned} R_{11}^{2f_1} &= \langle X_1(n) r_1^*(n) \rangle_N = \langle (\sin 2\pi f_1 n)^2 e^{-j2\pi 2f_1 n} \rangle_N \\ &+ \langle (\sin 2\pi f_2 n)^2 e^{-j2\pi 2f_1 n} \rangle_N + \langle n_1(n)^2 e^{-j2\pi 2f_1 n} \rangle_N \\ &+ 4 \cos(\theta_{11} - \theta_{10}) \langle s_1(n) s_2(n) \sin(2\pi f_1 n) \sin(2\pi f_2 n) e^{-j2\pi 2f_1 n} \rangle_N \\ &+ 4 \cos(\theta_{10}) \langle s_1(n) n_1(n) \sin(2\pi f_1 n) e^{-j2\pi 2f_1 n} \rangle_N \\ &+ 4 \cos(\theta_{11}) \langle s_2(n) n_1(n) \sin(2\pi f_2 n) e^{-j2\pi 2f_1 n} \rangle_N \end{aligned} \quad (D.5)$$

and

$$\begin{aligned}
 R_{21}^{2f_1} = & \langle X_1(n) r_{11}^*(n) \rangle_N = e^{j(\theta_{20} - \theta_{10})} \langle (\sin 2\pi f_1 n)^2 e^{-j2\pi 2f_1 n} \rangle_N \\
 & + e^{j(\theta_{21} - \theta_{11})} \langle (\sin 2\pi f_2 n)^2 e^{-j2\pi 2f_1 n} \rangle_N + \langle n_1(n) n_2(n) e^{-j2\pi 2f_1 n} \rangle_N \\
 & + \left(e^{j(\theta_{20} - \theta_{11})} + e^{j(\theta_{21} - \theta_{10})} \right) \langle s_1(n) s_2(n) \sin(2\pi f_1 n) \sin(2\pi f_2 n) e^{-j2\pi 2f_1 n} \rangle_N \\
 & + \langle (n_1(n) e^{j\theta_{20}} + n_2(n) e^{j\theta_{10}}) s_1(n) \sin(2\pi f_1 n) e^{-j2\pi 2f_1 n} \rangle_N \\
 & + \langle (n_1(n) e^{j\theta_{21}} + n_2(n) e^{j\theta_{11}}) s_2(n) \sin(2\pi f_2 n) e^{-j2\pi 2f_1 n} \rangle_N
 \end{aligned} \quad (D.6)$$

Generally, the individual time-average terms in (D.5) and (D.6) can be expressed in the form like

$$c_f = \langle f(n) e^{-j2\pi 2f_1 n} \rangle_N = \frac{1}{N} \sum_{n=0}^{N-1} f(n) e^{-j2\pi 2f_1 n} \quad (D.7)$$

which can be considered as the coefficient of a N-point Discrete Fourier Transformation under the expansion of $\exp(-j2\pi 2f_1 n)$. It is known that c_f does not equal to zero, if and only if there is an $\exp(j2\pi 2f_1 n)$ component in $f(n)$, otherwise c_f equal to zero. In this sense, all the terms except the first ones in (D.5) and (D.6) are equal to zero. In other words, these terms are not spectrally coherent at the frequency $2f_1$ [17]. Our interesting here is how these terms change with the increase of N, since it will provide us some insights into the adaptive behavior of the cyclic-correlation operation. It is difficult to find the specific formula for each term in (D.5) and (D.6), because of their randomness within the finite time. But the first two terms in (A.5) and (A.6) can be expressed in specific formula. If let $\text{sum}(1) = \langle (\sin(2\pi 2f_1 n))^2 \exp(-j2\pi 2f_1 n) \rangle_N$, and $\text{sum}(i) = \langle (\sin(2\pi 2f_i n))^2 \exp(-j2\pi 2f_1 n) \rangle_N$, ($i \neq 1$) from the definition, we have

$$\begin{aligned}
 \text{sum}(1) = & \langle (\sin 2\pi f_1 n)^2 e^{-j2\pi 2f_1 n} \rangle_N = \frac{1}{N} \sum_{n=0}^{N-1} \sin^2(2\pi f_1 n) e^{-j2\pi 2f_1 n} \\
 & = \frac{1}{4} + \frac{1}{2N} \frac{\exp(2\pi f_1 k(N-1)) \sin(2\pi f_1 N)}{\sin(2\pi f_1)} \\
 & \quad - \frac{1}{4N} \frac{\exp(4\pi f_1 k(N-1)) \sin(4\pi f_1 N)}{\sin(4\pi f_1)}
 \end{aligned} \quad (D.8)$$

and

$$\begin{aligned}
 \text{sum}(i) &= \langle \sin(2\pi f_i t)^2 e^{j2\pi 2f_1 t} \rangle_N = \frac{1}{N} \sum_{n=0}^{N-1} \sin(2\pi f_i t)^2 e^{j2\pi 2f_1 t} \\
 &= \frac{1}{4N} \left[\frac{\exp(j\pi(f_i - f_1)(N-1)) \sin(\pi(f_i - f_1)N)}{\sin(\pi(f_i - f_1))} + \right. \\
 &\quad \frac{\exp(-j\pi(3f_i + f_1)(N-1)) \sin(\pi(3f_i + f_1)N)}{\sin(\pi(3f_i + f_1))} - \\
 &\quad \frac{\exp(-j\pi(3f_1 - f_i)(N-1)) \sin(\pi(3f_1 - f_i)N)}{\sin(\pi(3f_1 - f_i))} - \\
 &\quad \left. \frac{\exp(-j\pi(f_i + f_1)(N-1)) \sin(\pi(f_i + f_1)N)}{\sin(\pi(f_i + f_1))} \right] \quad (D.9)
 \end{aligned}$$

Actually, if it is assumed that the signal powers of user and interference equal to 1, $\text{sum}(1)$ and $\text{sum}(i)$ are the cyclic-correlations of the desired user and interference signals at frequency separation $2f_1$. It is seen clearly from (D.8) and (D.9), that when N is larger, $\text{sum}(1)$ equal to -.25 and $\text{sum}(i)$ equal to zero. Hence, using the above results, we have

$$R_{11}^{2f_1} = \langle X_1(n) r_{*1}^*(n) \rangle_N = \langle (\sin 2\pi f_1 n)^2 e^{-j2\pi 2f_1 n} \rangle_N = \text{sum}(1) \quad (D.10)$$

$$\begin{aligned}
 R_{21}^{2f_1} &= \langle X_2(n) r_{*1}^*(n) \rangle_N = e^{j(\theta_{20} - \theta_{10})} \langle (\sin 2\pi f_1 n)^2 e^{-j2\pi 2f_1 n} \rangle_N \\
 &= e^{j(\theta_{20} - \theta_{10})} \text{sum}(1) \quad (D.11)
 \end{aligned}$$

and

$$R_1^{2f_1} = \begin{bmatrix} R_{11}^{2f_1} & R_{21}^{2f_1} \end{bmatrix}^T = \text{sum}(1) \begin{bmatrix} 1 \\ e^{j(\theta_{20} - \theta_{10})} \end{bmatrix}^T \quad (D.12)$$

(D.12) is an estimation of DOA of desired user comparing with A_1 in (D.2), since it also cophases the desired signal from two channels. So far, we presented the cyclic-correlation results for signal model in (D.2).

If the transmission signal is of form

$$u_i(n) = s_i(n) \exp(j2\pi f_i n) \quad i = 1, 2 \quad (\text{D.13})$$

and let

$$r_1(n) = X_1(n) e^{-j2\pi 2f_1 n} \quad (\text{D.14})$$

be the reference signal and $X_1(n)$ is same as defined in (D.1), following the same procedures as we did above and let s_i be the real data, we have

$$\begin{aligned} R_{11}^{2f_1} &= \langle X_1(n) r_1(n) \rangle_N = e^{j(\theta_{10} + \theta_{10})} \langle e^{j2\pi 2f_1 n} e^{-j2\pi 2f_1 n} \rangle_N \\ &+ e^{j(\theta_{11} + \theta_{11})} \langle e^{j2\pi 2f_2 n} e^{-j2\pi 2f_1 n} \rangle_N + \langle n_1(n)^2 e^{-j2\pi 2f_1 n} \rangle_N \\ &+ 4 \cos(\theta_{11} + \theta_{10}) \langle s_1(n) s_2(n) e^{j2\pi f_1 n} e^{j2\pi f_2 n} e^{-j2\pi 2f_1 n} \rangle_N \\ &+ 4 \cos(\theta_{10}) \langle s_1(n) n_1(n) e^{j2\pi f_1 n} e^{-j2\pi 2f_1 n} \rangle_N \\ &+ 4 \cos(\theta_{11}) \langle s_2(n) n_1(n) e^{j2\pi f_2 n} e^{-j2\pi 2f_1 n} \rangle_N \end{aligned} \quad (\text{D.15})$$

and

$$\begin{aligned} R_{21}^{2f_1} &= \langle X_1(n) r_1(n) \rangle_N = e^{j(\theta_{20} + \theta_{10})} \langle e^{j2\pi 2f_1 n} e^{-j2\pi 2f_1 n} \rangle_N \\ &+ e^{j(\theta_{21} + \theta_{11})} \langle e^{j2\pi 2f_2 n} e^{-j2\pi 2f_1 n} \rangle_N + \langle n_1(n) n_2(n) e^{-j2\pi 2f_1 n} \rangle_N \\ &+ \left(e^{j(\theta_{20} + \theta_{11})} + e^{j(\theta_{21} + \theta_{10})} \right) \langle s_1(n) s_2(n) e^{j2\pi f_1 n} e^{j2\pi f_2 n} e^{-j2\pi 2f_1 n} \rangle_N \\ &+ \langle \left(n_1(n) e^{j\theta_{20}} + n_2(n) e^{j\theta_{10}} \right) s_1(n) e^{j2\pi f_1 n} e^{-j2\pi 2f_1 n} \rangle_N \\ &+ \langle \left(n_1(n) e^{j\theta_{21}} + n_2(n) e^{j\theta_{11}} \right) s_2(n) e^{j2\pi f_2 n} e^{-j2\pi 2f_1 n} \rangle_N \end{aligned} \quad (\text{D.16})$$

Define,

$$\text{sum}(1) = \langle e^{j2\pi 2f_1 n} e^{-j2\pi 2f_1 n} \rangle_N = \frac{1}{N} \sum_{n=0}^{N-1} e^{j2\pi 2f_1 n} e^{-j2\pi 2f_1 n} = 1 \quad (\text{D.17})$$

and

$$\begin{aligned}
 \text{sum}(2) &= \frac{1}{N} \sum_{n=0}^{N-1} e^{j2\pi 2f_2 n} e^{-j2\pi 2f_1 n} = \\
 &= \frac{1}{N} \frac{\exp(j2\pi(f_2-f_1)N) \sin(2\pi(f_2-f_1)N)}{\sin(2\pi(f_2-f_1))}
 \end{aligned} \tag{D.18}$$

The (4.42) with two-element array in non-fading case can be rewritten as

$$\begin{aligned}
 \mathbf{R}_1^{2f_1} &= \begin{bmatrix} \mathbf{R}_{11}^{2f_1} & \mathbf{R}_{21}^{2f_1} \end{bmatrix}^T = \begin{bmatrix} \text{sum}(1) e^{j(\theta_{10} + \theta_{10})} & \text{sum}(1) e^{j(\theta_{20} + \theta_{10})} \end{bmatrix}^T \\
 &= e^{j(\theta_{10} + \theta_{10})} \begin{bmatrix} 1 & e^{j(\theta_{20} - \theta_{10})} \end{bmatrix}^T
 \end{aligned} \tag{D.19}$$

with the same explanation for (D.5) and (D.6).

In case of fading, we also have

$$\begin{aligned}
 \text{sum}(1) &= \langle \alpha_{10} \alpha_{10}^* (\sin 2\pi f_1 n)^2 e^{-j2\pi 2f_1 n} \rangle_N \\
 \text{sum}(2) &= \langle \alpha_{21} \alpha_{21}^* (\sin 2\pi f_2 n)^2 e^{-j2\pi 2f_1 n} \rangle_N
 \end{aligned} \tag{D.20}$$

if the transmission signal is given by (D.2) and .

$$\begin{aligned}
 \text{sum}(1) &= \langle \alpha_{11} \alpha_{11}^* \rangle_N \\
 \text{sum}(2) &= \langle \alpha_{22} \alpha_{22}^* e^{j2\pi f_2 n} e^{-j2\pi 2f_1 n} \rangle_N
 \end{aligned} \tag{D.21}$$

if the transmission signal is given by (D.13).

Appendix E. Cyclic-autocorrelation function based on finite data collection

Based on the data model represented in equation (3.1), assuming that $d_i(n)$ is a BPSK data sequence and $d_i(n)^2=1$, R_{ii}^α in equation (3.17) can be rewritten as

$$\begin{aligned}
 R_{ii}^\alpha &= \frac{1}{N} \sum_{k=1}^N s_i(k) s_i(k) e^{-j2\pi\alpha k} \\
 &= \frac{1}{N} \sum_{n=0}^{N-1} e^{j2\pi2f_2t} e^{-j2\pi2f_1t} \\
 &= \frac{1}{N} \frac{\exp(j2\pi(f_2-f_1)N) \sin(2\pi(f_2-f_1)N)}{\sin(2\pi(f_2-f_1))}
 \end{aligned} \tag{E.1}$$

For $f_2 = f_1$, $R_{ii}^\alpha = 1$. If $\Delta\alpha = f_2 - f_1 = 1/48$ as it is used in this paper, and $N \geq 3/\Delta\alpha$, then $|R_{ii}^\alpha| < 0.0531 \approx 0$. That is, after cyclic-correlation operation over $N \geq 3/\Delta\alpha$ period, the cyclic-autocorrelation function of interference at $a = 2*f_1$ approaches to zero and equation of (3.17) holds. Although equation (A.1) is derived for case of non-fading, simulation results show that the conclusion can also be extended to case of fading.

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