CAPACITY IMPROVEMENTS USING ADAPTIVE NULLSTEERING ANTENNAS IN IS-95 CELLULAR CDMA SYSTEMS

by

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We accept this thesis as conforming
to the required standard

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March 2002

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Date 21st Mar, 1992
Abstract

In this thesis, the effect of adaptive nullsteering on the system capacity of an IS-95 system is investigated. Adaptive nullsteering is a Spatial Division Multiple Access (SDMA) technology which can be used to increase the system capacity by exploiting a new spatial dimension. By using this SDMA smart antenna with Code Division Multiple Access (CDMA), the system capacity can be increased significantly. In order to simulate and compare the performance of adaptive algorithms in the IS-95 receivers, both IS-95 uplink and downlink are simulated at chip level. Classical adaptive algorithms such as Direct Matrix Inversion (DMI), Least Mean Square (LMS) and Recursive Least Square (RLS) are modified accordingly to conform to this IS-95 receiver architecture. With this receiver structure, performances between different adaptive nullsteering algorithms and that without smart antenna are compared in terms of Signal-to-Interference Ratio (SIR) and their convergence rate to the steady-state SIR.

Based on these performance results, a power method is proposed which can be used to estimate the IS-95 system capacity efficiently in a multiple-cell scenario without performing Monte-Carlo simulation. Realistic urban multipath models are used in the simulation to obtain accurate system capacity results. From these results, the advantages of adaptive nullsteering over that without smart antenna are presented. In addition, the performances of adaptive nullsteering and beamforming are also compared in terms of IS-95 system capacity. It is shown that both adaptive nullsteering and beamforming have their own advantages in different urban environments.
# Table of Contents

Abstract ii  
List of Tables vii  
List of Figures ix  
List of Abbreviations xiii  
List of Symbols xv  
Acknowledgment xx  

Chapter 1 INTRODUCTION 1  

Chapter 2 SMART ANTENNA TECHNOLOGY 8  

2.1 Introduction ........................................................................................................ 8  
2.2 Omnidirectional Antennas .............................................................................. 8  
2.3 Sectored Antennas ........................................................................................ 9  
2.4 Adaptive Antennas ........................................................................................ 10  
2.4.1 Multiple-Sensor Antenna Array ................................................................. 11  
2.4.2 Adaptive Antenna Architecture ................................................................. 16  
2.4.3 Beamforming ............................................................................................ 17  
2.4.4 Nullsteering .............................................................................................. 20  
2.4.5 Adaptive Nullsteering ............................................................................... 22  
2.5 Recursive Approach for Real Time Adaptive Nullsteering ....................... 31  
2.5.1 Direct Matrix Inversion (DMI) .................................................................. 34  
2.5.2 Least Mean Square Error (LMS) ............................................................... 36  
2.5.3 Recursive Least Square (RLS) ................................................................. 38  
2.6 Conclusions ..................................................................................................... 40
<table>
<thead>
<tr>
<th>Chapter 3</th>
<th>CHANNEL MODELLING</th>
<th>42</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.1 Introduction</td>
<td></td>
<td>42</td>
</tr>
<tr>
<td>3.2 Large-Scale Fading</td>
<td></td>
<td>42</td>
</tr>
<tr>
<td>3.2.1 Propagation Loss</td>
<td></td>
<td>42</td>
</tr>
<tr>
<td>3.2.2 Lognormal Shadowing</td>
<td></td>
<td>44</td>
</tr>
<tr>
<td>3.3 Small-Scale Fading</td>
<td></td>
<td>45</td>
</tr>
<tr>
<td>3.3.1 Uncorrelated Rayleigh Fading</td>
<td></td>
<td>47</td>
</tr>
<tr>
<td>3.3.2 Correlated Rayleigh Fading</td>
<td></td>
<td>48</td>
</tr>
<tr>
<td>3.4 Scattering Model</td>
<td></td>
<td>56</td>
</tr>
<tr>
<td>3.5 Conclusions</td>
<td></td>
<td>56</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Chapter 4</th>
<th>AN OVERVIEW OF THE IS-95 STANDARD</th>
<th>58</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.1 Introduction</td>
<td></td>
<td>58</td>
</tr>
<tr>
<td>4.2 Direct Sequence (DS) Spread Spectrum Technique</td>
<td></td>
<td>58</td>
</tr>
<tr>
<td>4.3 The IS-95 Uplink Traffic Channel</td>
<td></td>
<td>61</td>
</tr>
<tr>
<td>4.4 The IS-95 Downlink Traffic Channel</td>
<td></td>
<td>62</td>
</tr>
<tr>
<td>4.5 The IS-95 Receiver for the Uplink</td>
<td></td>
<td>64</td>
</tr>
<tr>
<td>4.6 The IS-95 Receiver for the Downlink</td>
<td></td>
<td>64</td>
</tr>
<tr>
<td>4.7 Individual Blocks in the IS-95 Transceiver</td>
<td></td>
<td>66</td>
</tr>
<tr>
<td>4.7.1 Introduction</td>
<td></td>
<td>66</td>
</tr>
<tr>
<td>4.7.2 Modulation</td>
<td></td>
<td>66</td>
</tr>
<tr>
<td>4.7.3 PN Random Sequence</td>
<td></td>
<td>67</td>
</tr>
<tr>
<td>4.7.4 Walsh Code Generator</td>
<td></td>
<td>69</td>
</tr>
<tr>
<td>4.7.5 Convolutional Encoder</td>
<td></td>
<td>71</td>
</tr>
</tbody>
</table>
## Chapter 5  PERFORMANCE OF NULLSTEERING ADAPTIVE ALGORITHMS FOR IS-95 CDMA SYSTEMS

<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.1</td>
<td>Introduction</td>
<td>76</td>
</tr>
<tr>
<td>5.2</td>
<td>IS-95 Uplink Traffic Channel Transmitter</td>
<td>77</td>
</tr>
<tr>
<td>5.3</td>
<td>IS-95 Uplink Traffic Channel Receiver</td>
<td>78</td>
</tr>
<tr>
<td>5.4</td>
<td>IS-95 Downlink Traffic Channel Transmitter</td>
<td>89</td>
</tr>
<tr>
<td>5.5</td>
<td>IS-95 Downlink Traffic Channel Receiver</td>
<td>90</td>
</tr>
<tr>
<td>5.6</td>
<td>The Adaptive Nullsteering Estimator</td>
<td>93</td>
</tr>
<tr>
<td>5.7</td>
<td>Modified Adaptive Algorithms</td>
<td>94</td>
</tr>
<tr>
<td>5.7.1</td>
<td>Modified DMI Algorithm</td>
<td>94</td>
</tr>
<tr>
<td>5.7.2</td>
<td>Modified LMS Error Algorithm</td>
<td>96</td>
</tr>
<tr>
<td>5.7.3</td>
<td>Modified RLS Algorithm</td>
<td>96</td>
</tr>
<tr>
<td>5.8</td>
<td>Convergence Performance of the DMI, LMS and RLS Algorithms</td>
<td>97</td>
</tr>
<tr>
<td>5.9</td>
<td>The Power Method</td>
<td>107</td>
</tr>
<tr>
<td>5.9.1</td>
<td>Introduction</td>
<td>107</td>
</tr>
<tr>
<td>5.9.2</td>
<td>Derivation of Power Method for Single-Path and Multipath Environment</td>
<td>107</td>
</tr>
<tr>
<td>5.10</td>
<td>Conclusions</td>
<td>110</td>
</tr>
</tbody>
</table>

## Chapter 6  SYSTEM CAPACITY ESTIMATION: METHODOLOGY, RESULTS AND DISCUSSION

<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>6.1</td>
<td>Introduction</td>
<td>112</td>
</tr>
<tr>
<td>6.2</td>
<td>Simulation Parameters and Methodology</td>
<td>112</td>
</tr>
<tr>
<td>6.2.1</td>
<td>Simulation Parameters</td>
<td>112</td>
</tr>
</tbody>
</table>
## List of Tables

| Table 2.1 | SIR comparison between beamforming, nullsteering and adaptive nullsteering with 3 users. INF represents very large number | 33 |
| Table 2.2 | SNR comparison between beamforming, nullsteering and adaptive nullsteering with 3 users, noise Power = 0.1W | 33 |
| Table 2.3 | SIR comparison between beamforming, nullsteering and adaptive with 5 users | 33 |
| Table 2.4 | SNR comparison between beamforming, nullsteering and adaptive nullsteering with 5 users, noise Power = 0.1W | 33 |
| Table 6.1 | Average system capacity results for adaptive nullsteering antennas with 1, 2, 4 and 8 omnidirectional antenna elements in a 19-cell single-path uplink environments | 126 |
| Table 6.2 | Average system capacity results for omnidirectional antenna, ideal 3-sectored antenna and adaptive nullsteering antenna with four 3-sectored antenna elements in a 19-cell single-path uplink environments | 128 |
| Table 6.3 | Average system capacity results for adaptive nullsteering using 4 and 8 omnidirectional antenna elements in a 19-cell single-path, uplink and downlink environments | 129 |
| Table 6.4 | Average system capacity results for adaptive nullsteering using 4 omnidirectional antenna elements in single-cell, 7-cell and 19-cell single-path uplink environments | 131 |
| Table 6.5 | Average system capacity results for adaptive nullsteering using four omnidirectional 3-sectored antenna elements array in single-cell, 7-cell and 19-cell single-path uplink environments | 132 |
| Table 6.6 | Average system capacity results for adaptive nullsteering using 4 omnidirectional antenna elements array in 19-cell, multipath uplink environments | 134 |
| Table 6.7 | Average system capacity results for adaptive nullsteering using 4 omnidirectional antenna elements array in 7-cell, multipath uplink environments | 136 |
| Table 6.8 | Average system capacity results for adaptive nullsteering antenna using 4 omnidirectional antenna elements array in single-cell, multipath uplink environments | 137 |
Table 6.9  Average system capacity results for beamforming using 1, 2, 4 and 8 omnidirectional antenna elements in a 19-cell single-path uplink environments ........................................................................................................... 138

Table 6.10  Average system capacity results for beamforming and adaptive nullsteering using four omnidirectional antenna elements array in 19-cell, multipath uplink environments. The system capacity results for adaptive nullsteering is taken from Table 6.6 and included here for convenient comparison with the results for beamforming ........................................................................................................... 141
**List of Figures**

| Fig. 2.1 | Normalized gain pattern of an omnidirectional antenna | 9 |
| Fig. 2.2 | Normalized gain pattern of a 3-sectored antenna | 10 |
| Fig. 2.3 | A circular array antenna consisting of eight antenna elements | 12 |
| Fig. 2.4 | An uniform linear array (ULA) with $M$ elements with reference point at the first element. $\lambda$ is the wavelength of the receiving signal | 13 |
| Fig. 2.5 | System architecture of adaptive antenna | 17 |
| Fig. 2.6 | Examples of normalized beamforming antenna pattern with maximum antenna gain steered to the AOA of each user at $20^\circ$, $30^\circ$ and $50^\circ$ | 19 |
| Fig. 2.7 | Examples of normalized nullsteering antenna Pattern with the antenna pattern optimized for users at $20^\circ$, $30^\circ$ and $50^\circ$. For example, for the signal of the desired user arriving at $20^\circ$, the nulls are placed at $30^\circ$ and $50^\circ$ in the antenna pattern | 23 |
| Fig. 2.8 | MMSE adaptive nullsteering block diagram | 24 |
| Fig. 2.9 | Examples of normalized adaptive nullsteering antenna pattern with the antenna pattern optimized for each of the users at $20^\circ$, $30^\circ$ and $50^\circ$. For example, for the signal of the desired user arriving at $20^\circ$, the nulls are placed at $30^\circ$ and $50^\circ$ in the antenna pattern. Noise power = $0.1$ W | 32 |
| Fig. 2.10 | Block diagram of adaptive antenna receiver using LMS | 37 |
| Fig. 3.1 | Multipath fading due to multipath reflections. $\tau$ denotes the different delays for the signals to travel from the mobile users to the basestation | 46 |
| Fig. 3.2 | The root mean squared (RMS) amplitude of Rayleigh fading when the mobile is travelling at 5km/hr, 15km/hr, 30km/hr and 50km/hr. For presentation purposes, the time unit is presented in terms of Walsh symbols to show the variation of amplitude in each Walsh symbol period. The entire time span in second is 0.52s | 50 |
| Fig. 3.3 | Magnified version of Rayleigh fading amplitude for mobile travelling at 50 km/hr | 51 |
| Fig. 3.4 | Frequency selective multipath channel model combined with Hashemi |
model ..........................................................54

Fig. 3.5 Geometrically based circular scattering model with scattering radius $r$...56

Fig. 4.1 Direct sequence (DS) spread spectrum System. (a) The original frequency spectrum (left) is spread when modulated by a PN sequence (right). (b) The time domain of the transmitted signal (left) when modulated by a PN sequence (right). (c) At the receiver, the jamming spectrum (left) is narrowed and lowered after filtering and despreading by the PN sequence. The received signal spectrum is recovered to original amplitude after despreading (right).................60

Fig. 4.2 Frame structure of the IS-95 uplink traffic channel..........................62

Fig. 4.3 Frame structure of the IS-95 downlink traffic channel.......................63

Fig. 4.4 IS-95 uplink receiver with $L$ Rake fingers.....................................65

Fig. 4.5 IS-95 downlink receiver with $L$ Rake fingers..................................65

Fig. 4.6 Short PN sequence linear feedback shift register block diagram.............68

Fig. 4.7 Long PN sequence linear feedback shift register block diagram.............69

Fig. 4.8 Convolutional encoder for the uplink with rate $r = 1/3$ and constraint length $K = 9$.................................................................72

Fig. 4.9 Convolutional encoder for the downlink with rate $r = 1/2$ and constraint length $K = 9$.................................................................73

Fig. 4.10 General block diagram of IS-95 Rake receiver ...............................75

Fig. 5.1 IS-95 Uplink traffic channel transmitter...........................................77

Fig. 5.2 IS-95 uplink traffic channel adaptive receiver.................................79

Fig. 5.3 Block diagram of the $\zeta$-th finger for the $m$-th antenna element..........80

Fig. 5.4 Block diagram of the $\zeta$-th nullsteering processor............................81

Fig. 5.5 Block diagram of the $\zeta$-th adaptive nullsteering weight vector estimator 82

Fig. 5.6 Block diagram of the Rake receiver using maximal ratio combining .......82

Fig. 5.7 Simplified IS-95 downlink traffic channel transmitter. For simplicity, the scrambler is omitted in the simulation...............................89
Fig. 5.8 IS-95 forward traffic channel coherent receiver for single-path environment ..........................................................91

Fig. 5.9 Comparison of convergence performance between DMI, RLS, LMS, power method and that without adaptive antenna in static environment, single-path uplink traffic channel ...........................................98

Fig. 5.10 Comparison of the convergence performances between DMI, RLS, LMS, power method and that without adaptive antenna in Rayleigh fading, single-path uplink traffic channel ..............................................101

Fig. 5.11 Comparison of the convergence performances between DMI, RLS, LMS, power method and that without adaptive antenna in Rayleigh fading environment in a multipath uplink traffic channel ..................102

Fig. 5.12 Comparison of the convergence performances between DMI, RLS, LMS, power method and that without adaptive antenna in a static environment in a single-path downlink traffic channel ......................105

Fig. 5.13 Comparison of the convergence performances between DMI, RLS, LMS, power method and that without adaptive antenna in a Rayleigh fading, a single-path downlink traffic channel .............................................106

Fig. 6.1 A 3-tier cell structure consisting of 19 hexagonal cells. r is the radius of each hexagonal cell .................................................................113

Fig. 6.2 Simulation flow diagram for pre-estimation of the system parameters of basestations and users ......................................................115

Fig. 6.3 Simulation flow diagram for estimating the uplink system capacity .......117

Fig. 6.4 Simulation flow diagram for estimating the downlink system capacity..120

Fig. 6.5 Uplink single-path system capacity results using adaptive nullsteering smart antenna with omnidirectional antenna elements ........126

Fig. 6.6 Uplink single-path system capacity results using ideal 3-sectored antenna and adaptive nullsteering smart antenna with four 3-sectored omnidirectional antenna elements .................................................128

Fig. 6.7 Single-path uplink and downlink system capacity results using 19-cell model employing adaptive nullsteering smart antenna ...........129

Fig. 6.8 Comparison of single-path uplink system capacity employing four omnidirectional antenna elements using adaptive nullsteering in a
single cell (1 cell), 2-tier cell (7 cell) and 3-tier cell (19 cell) model ......131

Fig. 6.9 Comparison of single-path uplink system capacity employing four omnidirectional 3-sectored antenna elements using adaptive nullsteering in a single cell (1 cell), 2-tier cell (7 cell) and 3-tier cell (19 cell) model ........................................................................132

Fig. 6.10 The multipath uplink system capacity results using adaptive nullsteering with four omnidirectional antenna elements in a 19-cell model .........................................................................................................................134

Fig. 6.11 Multipath uplink system capacity results using adaptive nullsteering with four omnidirectional antenna elements in a 7-cell model ..................136

Fig. 6.12 Multipath uplink system capacity results using adaptive nullsteering with four omnidirectional antenna elements in a single-cell model .........137

Fig. 6.13 Uplink single-path system capacity results using beamforming smart antenna with 2, 4 and 8 omnidirectional antenna elements .........................138

Fig. 6.14 Multipath uplink system capacity results using beamforming with four omnidirectional antenna elements in a 19-cell model ......................141
## List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AOA</td>
<td>Angle of Arrival</td>
</tr>
<tr>
<td>AMPS</td>
<td>Advanced Mobile Phone Service</td>
</tr>
<tr>
<td>AWGN</td>
<td>Additive White Gaussian Noise</td>
</tr>
<tr>
<td>BER</td>
<td>Bit Error Rate</td>
</tr>
<tr>
<td>BPSK</td>
<td>Binary Phase Shift Keying</td>
</tr>
<tr>
<td>CDMA</td>
<td>Code Division Multiple Access</td>
</tr>
<tr>
<td>CER</td>
<td>Chip Error Rate</td>
</tr>
<tr>
<td>CRC</td>
<td>Cyclic Redundancy Check</td>
</tr>
<tr>
<td>DMI</td>
<td>Direct Matrix Inversion</td>
</tr>
<tr>
<td>DS</td>
<td>Direct Sequence</td>
</tr>
<tr>
<td>FDMA</td>
<td>Frequency Division Multiple Access</td>
</tr>
<tr>
<td>FEC</td>
<td>Forward Error Control</td>
</tr>
<tr>
<td>GBCM</td>
<td>Geometrically Based Circular Model</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographical Information System</td>
</tr>
<tr>
<td>GSM</td>
<td>Global System for Mobile communications</td>
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<tr>
<td>JTACS</td>
<td>Japanese Total Access Communication System</td>
</tr>
<tr>
<td>LMS</td>
<td>Least Mean Square</td>
</tr>
<tr>
<td>MMSE</td>
<td>Minimum Mean Square Error</td>
</tr>
<tr>
<td>MSINR</td>
<td>Maximal Signal-to-Interference-plus-Noise Ratio</td>
</tr>
<tr>
<td>MVDR</td>
<td>Minimum Variance Distortionless Response</td>
</tr>
<tr>
<td>OQPSK</td>
<td>Offset Quadrature Phase Shift Keying</td>
</tr>
<tr>
<td>PN</td>
<td>Pseudorandom Noise</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>--------------------------------------</td>
</tr>
<tr>
<td>QPSK</td>
<td>Quadrature Phase Shift Keying</td>
</tr>
<tr>
<td>RLS</td>
<td>Recursive Least Squared</td>
</tr>
<tr>
<td>SDMA</td>
<td>Spatial Division Multiple Access</td>
</tr>
<tr>
<td>SIR</td>
<td>Signal-to-Interference Ratio</td>
</tr>
<tr>
<td>SINR</td>
<td>Signal-to-Interference-plus-Noise Ratio</td>
</tr>
<tr>
<td>SNR</td>
<td>Signal-to-Noise Ratio</td>
</tr>
<tr>
<td>TACS</td>
<td>Total Access Communication System</td>
</tr>
<tr>
<td>TDMA</td>
<td>Time Division Multiple Access</td>
</tr>
<tr>
<td>ULA</td>
<td>Uniform-calibrated Linear Array</td>
</tr>
</tbody>
</table>
# List of Symbols

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x(t)$</td>
<td>Incoming Signal</td>
</tr>
<tr>
<td>$a(t)$</td>
<td>Incoming Signal Amplitude</td>
</tr>
<tr>
<td>$\phi(t)$</td>
<td>Incoming Signal Phase</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Instantaneous Phase</td>
</tr>
<tr>
<td>$f_c$</td>
<td>Carrier Frequency</td>
</tr>
<tr>
<td>$d_i$</td>
<td>Perpendicular Distance between Wavefront and the $i$-th Antenna Element</td>
</tr>
<tr>
<td>$M$</td>
<td>Total Number of Antenna Elements</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Wave Length</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Angle between Incoming Wavefront and Antenna Array</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Array Response Vector</td>
</tr>
<tr>
<td>$v$</td>
<td>Spatial Frequency</td>
</tr>
<tr>
<td>$N$</td>
<td>Total Number of Users</td>
</tr>
<tr>
<td>$a_n$</td>
<td>Received Signal Amplitude of the $n$-th user</td>
</tr>
<tr>
<td>$\phi_{i,n}$</td>
<td>Array Response Vector of the $n$-th user at the $i$-th Antenna Element</td>
</tr>
<tr>
<td>$\theta_n$</td>
<td>Angle of Arrival of the $n$-th user</td>
</tr>
<tr>
<td>$x$</td>
<td>Received Signal Vector</td>
</tr>
<tr>
<td>$w$</td>
<td>Adaptive Weight Vector</td>
</tr>
<tr>
<td>$\Gamma$</td>
<td>Beam Steering Matrix</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Mean Square Error</td>
</tr>
</tbody>
</table>
\( y_d \) Desired Signal Reference

\( r_{xd} \) Cross-correlation Vector between received signal vector \( x \) and Desired Signal Reference \( y_d \)

\( R_{xx} \) Autocorrelation Matrix of Received Signal Vector

\( s \) Received Response Column Vector

\( R_{ss} \) Autocorrelation Matrix of Desired Signal after Weighting

\( R_{NI} \) Autocorrelation Matrix of Interference-plus-Noise

\( \hat{R}_{NI} \) Sample Autocorrelation Matrix of Interference-plus-Noise

\( \hat{R}_{xx} \) Sample Autocorrelation Matrix of Received Signal Vector

\( \hat{r}_{xd} \) Sample Cross-correlation Vector between received signal vector \( x \) and Desired Signal Reference \( y_d \)

\( \kappa \) Attenuation Factor

\( L \) Standard Medium Path Loss in dB

\( h_{te} \) Effective Basestation Antenna Height in meter

\( h_{re} \) Effective Mobile Antenna Height in meter

\( a(h_{te}) \) Correction Factor for Effective Mobile Antenna Height

\( e_i \) \( i \)-th Partial Wave Amplitude

\( \varphi_i \) \( i \)-th Partial Wave Original Phase

\( k \) Number of Partial Waves
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>Rayleigh Amplitude</td>
</tr>
<tr>
<td>$\beta_k$</td>
<td>Rayleigh Amplitude of the $k$-th path</td>
</tr>
<tr>
<td>$\vartheta$</td>
<td>Rayleigh Correlated Phase</td>
</tr>
<tr>
<td>$\eta_k$</td>
<td>Hashemi Model Phase for the $k$-th path</td>
</tr>
<tr>
<td>$b(t)$</td>
<td>Transmission Bit</td>
</tr>
<tr>
<td>$a_k$</td>
<td>Amplitude Impulse Response of Channel</td>
</tr>
<tr>
<td>$P_k$</td>
<td>Hashemi Average Power Bin for the $k$-th path</td>
</tr>
<tr>
<td>$\tau_k$</td>
<td>Path Delay of the $k$-th path</td>
</tr>
<tr>
<td>$\Phi_k$</td>
<td>Combined Phase of the $k$-th path</td>
</tr>
<tr>
<td>$W$</td>
<td>Channel Bandwidth</td>
</tr>
<tr>
<td>$T_s$</td>
<td>Symbol Period</td>
</tr>
<tr>
<td>$T_c$</td>
<td>Chip Period</td>
</tr>
<tr>
<td>$s^{(k)}(t)$</td>
<td>Transmitted Signal for the $k$-th user</td>
</tr>
<tr>
<td>$c_{L}^{(k)}(t)$</td>
<td>Long PN Signature of the $k$-th user</td>
</tr>
<tr>
<td>$c_{S}^{(k)}(t)$</td>
<td>Short PN Signature of the $k$-th user</td>
</tr>
<tr>
<td>$H_{h}^{(k)}(t)$</td>
<td>$h$-th Walsh Code for the $k$-th user</td>
</tr>
<tr>
<td>$E_b$</td>
<td>Bit Energy</td>
</tr>
<tr>
<td>$T_w$</td>
<td>Walsh Chip Duration</td>
</tr>
<tr>
<td>$r_m(t)$</td>
<td>Complex Input Signal at the $j$-th Antenna Element</td>
</tr>
</tbody>
</table>
\( r_{\zeta,m}^{(k)}(t) \) Time-aligned Received Signal at the \( \zeta \)-th Rake Finger of the \( m \)-th Antenna Element with reference to the \( k \)-th user

\( b_{h,m,\zeta}^{(k)} \) Correlated Value at the \( \zeta \)-th Rake Finger of the \( m \)-th Antenna Element with reference to the \( k \)-th user

\( w_{m,\zeta}^{(k)} \) Complex Weight at the \( \zeta \)-th Rake Finger of the \( m \)-th Antenna Element with reference to the \( k \)-th user

\( L_r \) Total Number of Rake Finger

\( p_i^{(k)} \) Average Transmitted Power at the \( i \)-th Rake Finger for the \( k \)-th user

\( \rho_i^{(k)} \) Rayleigh Amplitude at the \( i \)-th Rake Finger for the \( k \)-th user

\( u_i \) \( i \)-th Decision Variable at the Output of Rake Receiver

\( H_h(t) \) Estimated Transmitted Walsh Sequence

\( x_{\zeta,m}^{(k)} \) Signal after Despreading at the \( \zeta \)-th Finger of the \( m \)-th Antenna Element with reference to the \( k \)-th user

\( \tau_i^{(n)} \) Path Delay of the \( i \)-th path for the \( n \)-th user

\( \varphi_i^{(n)} \) Correlated Channel Phase Shift of the \( i \)-th path for the \( n \)-th user

\( \alpha_i^{(n)} \) Angle of Arrival of the \( i \)-th path for the \( n \)-th user

\( S_{\zeta,m}^{(k)}(t) \) Desired Signal at the \( \zeta \)-th Rake Finger of the \( m \)-th Antenna Element with reference to the \( k \)-th user

\( I_{\text{ma}(\zeta,m)}^{(k)}(t) \) Multiple Access Interference at the \( \zeta \)-th Rake Finger of the \( m \)-th Antenna Element with reference to the \( k \)-th user
\( I_{si(\zeta, m)}^{(k)}(t) \) Self Interference at the \( \zeta \)-th Rake Finger of the \( m \)-th Antenna Element with reference to the \( k \)-th user

\( \tau_{i, \zeta}^{(n)} \) Path Delay of the \( i \)-th path for the \( n \)-th user relative to the \( \zeta \)-th path for the \( k \)-th user

\( \varphi_{i, \zeta}^{(n)} \) Phase Delay of the \( i \)-th path for the \( n \)-th user relative to the \( \zeta \)-th path for the \( k \)-th user

\( \gamma_{n}^{(k)} \) Power Modification Factor optimized for the \( n \)-th user to the \( k \)-th user
Acknowledgment

Though this thesis takes longer time to finish than I expect, and in between there are so many obstacles arising that forbid me to continue, I would like to take this chance to express my thanks towards first of all my Lord Jesus Christ, who is always by my side and gives me strength to press on, re-ignites my hope and enables me to do all things through Him who strengthens me. Secondly, I am overwhelmed by the understanding and love from my beloved family, who recently has immigrated to Canada and is in desperate need of my help in starting a company. I, being completely concentrated on the research work, offer very little help indeed, yet they still fully support me by all means - spiritually, emotionally and physically. Professor P. Takis Mathiopoulos, who is my supervisor, is the other person that I would like to give thanks. I thank him so much for his gentleness, guidance and friendliness throughout my whole research, as well as providing funding support during this period. Dr. Andrew S. Wright from Datum Telegraphics Inc., who is another kind person and has collaborated with Prof. Mathiopoulos on this research group project, offers tremendous technical support and resources that can never be forgotten. I always remember how he sacrifices his own lunch time to solve my research problem. There are many other colleagues who help me throughout my research by putting their research aside and giving me suggestion. I would like to thank Mr. Lester Chan, who has done research on beamforming, offering his work for me as a guideline and giving me technical support; Mr. Norman Chan, who although is now with Motorola, continues to give me support through email; Mr. Peter Chong, who offers software tutorial to me and last but not the least, my mentor Mr. Vincent Wong, who encourages me by all means. There are a whole lot of other people that I would like to say thank you and I apologize for not listing out all your names due to size limitation. Without you, this thesis cannot be a reality.
Chapter 1 INTRODUCTION

Cellular telecommunication systems have gone through a long series of evolution. In mid-1980s, first generation system such as Advanced Mobile Phone Service (AMPS) in the United States, Total Access Communication System (TACS) in Europe and Japanese Total Access Communication System (JTACS) in Japan were developed. Frequency Division Multiple Access (FDMA) was employed for these analog systems to increase the system capacity by allocating users to different frequency channels [29]. However, when users started to increase dramatically, traditional means to increase the system capacity, such as shrinking cell size and adding more basestations with the use of FDMA, are not sufficient to support this increasing number of users. As a result of that, from about 1996 onwards, second generation systems started to gain momentum by providing digital voice and messaging services. These systems included Global System for Mobile communications (GSM) / DCS-1900, IS-95 and US TDMA-136 [48]. By using Time Division Multiple Access (TDMA) in the GSM system, different users can share the same frequency channel but on different time slots [29]. The spectrum efficiency and therefore the system capacity can be further increased by using Code Division Multiple Access (CDMA). CDMA is used in the IS-95 system and has become very popular as it allows users to share the same frequency channel and time slot. CDMA appears to give a higher system capacity than FDMA and TDMA as presented in [1].

To further increase the system capacity provided by the IS-95 system, Spatial Division Multiple Access (SDMA) [2][3][4] is used as a hybrid multiple access technique in conjunction with CDMA [5]. As CDMA does not exploit the multiplicity of spatial channels which arises because each user occupies an unique spatial location, SDMA exploits this dimension and allows
multiple users within the same radio cell to be allocated on the same frequency channel and time slot. In SDMA, the so-called smart antenna technology is being used to change the antenna pattern dynamically so as to maintain acceptably high Signal-to-Noise Ratios (SNR) and/or Signal-to-Interference-plus-Noise Ratios (SINR) [7][48]. This can be achieved by steering the main beam of the antenna to the direction of the desired user and this method is known as beamforming [6]. However, beamforming is suboptimal when the number of users in the system is not very large and the user distribution is not uniform leading to a large gap between the maximum SINR and the maximum SNR [7]. As a result of that, another SDMA technique called nullsteering [7][8] is used to direct the nulls in the antenna pattern to the Angle Of Arrival (AOA) of interferers. However, nullsteering has a limitation that the number of nulls created cannot be greater than the number of antenna sensors used [2]. Therefore, a special form of nullsteering, which is known as adaptive nullsteering [7], can be applied to improve the received SINR by adaptively changing the antenna pattern, resulting in a higher system capacity. This method will be considered in this thesis.

The effects of beamforming on the system capacity of CDMA systems have been studied extensively in the past (see for example [9][10]). However, due to the difficulty in analyzing the distribution function of the SINR for the case of more than one interferer [7], it appears that relatively less research has been conducted on estimating the capacity of the system with adaptive nullsteering smart antennas (e.g. [11]). Consequently, the capacity evaluation results for these systems are seldom expressed as closed-form expressions but are usually found by computer simulations instead and are presented as numerical results. In such simulations, the adaptive algorithms and the associated hardware are often assumed to be implementable. It should be noted that although classical algorithms such as direct matrix inversion (DMI) [7][12][13][14], least
mean square error (LMS) \([7][13][14][15]\) and recursive least squared (RLS) \([7][15]\) algorithms enable the received SINR at the basestation to reach its steady-state, these algorithms require either significant amount of computational complexity or converge slowly. The slow convergence rate is especially a problem when the environment is fast-changing. This results in failure to converge to the steady-state in time, and this in turn gives non-optimal SINR, thus yielding lower system capacities. Because of these constraints, research is conducted in investigating algorithms that minimize the computational complexity required in realizing the adaptive algorithms yet enable fast convergence rate to the optimal SNR or SINR at the same time. A recent example being that of Shiu \([16]\) who has developed a noniterative signal subspace eigenstructure update enabling low-complexity recursive processing of beamforming weight vectors.

In addition to developing these algorithms, active research has been conducted to estimate the required parameters for optimal SINR efficiently and accurately. Direction-finding methods such as MUSIC \([17]\) and ESPRIT \([18]\) are used to estimate the AOA of users, which is essential in calculating the weight vector which gives optimal SINR. However, when the number of users far exceeds the number of antennas, these methods cannot be used as they require certain assumptions on the number of signal wavefronts arriving at the basestation \([19]\). In light of this, Naguib \([19]\) developed a code filtering technique which used the pre-correlation and post-correlation signal matrices to solve for the noise-plus-interference covariance matrix and the array response vector. Later, Earnshaw \([11]\) improved the algorithm by using feedback correlation beamforming which reduced errors in the estimates of the pre-correlation and post-correlation signal matrices. Luo \([20]\) further improved the finite sample performance of the pre-correlation and post-correlation autocovariance matrix by using signal cancellation technique. However, the inherent complexity of these algorithms makes them unsuitable for simulating and estimating the capacity.
Chapter 1 INTRODUCTION

of complex telecommunication systems (such as the IS-95 system which will be considered in this thesis). As a result, assumptions such as single-path or equal energy distribution in each multipath component are often made [11],[21]. With these assumptions, optimistic results are usually obtained because firstly signals are transmitted in multipaths in urban environments and secondly, the distribution of energy in different paths is usually different.

Motivated by the above, this thesis presents a comprehensive study of the performance improvements in system capacity SDMA technique can offer in practical IS-95 CDMA systems. The improvements of beamforming and adaptive nullsteering SDMA technologies in the system capacity will be compared. As mentioned before, since the system capacities are oftenly difficult to be expressed in closed forms, instead simulations are performed to estimate the overall system capacity. However, since simulating system capacity, especially in conjunction with adaptive antennas, is often a resource consuming and tedious task, the adaptive nullsteering algorithm must be appropriately simulated to facilitate efficient system capacity estimations. In order to address these technical issues, the thesis is divided into two parts. The first part is devoted to demonstrate that there exist algorithms which enable the weight vector to converge rapidly even in a Rayleigh fading environment. For this purpose, two IS-95 smart antenna receivers for both the downlink and uplink are employed. By using these simulators in conjunction with adaptive algorithms such as DMI, LMS and RLS, the convergence and steady-state performances of these adaptive algorithms are simulated. Based upon these results, a power method is proposed which can be used to simulate the system capacity of a multiple-cell IS-95 system for both uplink and downlink efficiently. The second part is to apply this power method in the system capacity simulation. In order to obtain realistic and accurate system capacity results for multipath urban environments, different sets of multipath power profiles for different urban channel models are calculated.
according to the work of Hashemi [22] instead of using equal energy distribution, which is often used for the sake of simplicity, in each of the paths.

The major contributions of this thesis can be summarized as follows:

• Adaptive algorithms such as DMI, LMS and RLS are modified to be used in conjunction with IS-95 downlink and uplink receiver. By using such adaptive nullsteering smart antenna in these receivers, it is shown that the received SINR can be dramatically increased.

• The convergence performance between DMI, LMS, RLS and that without adaptive antenna are compared.

• For simulating the adaptive nullsteering antenna efficiently, a power method is proposed and analyzed. Through this method, the system capacity of the IS-95 system can be effectively estimated.

• Accurate system capacity results have been obtained for both downlink and uplink. Performance comparisons are made between systems which employ beamforming, adaptive nullsteering or without smart antenna.

The organization of the thesis is as follows.

Chapter 2 will give an introduction on different antenna technologies and configurations, including the omnidirectional antenna, 3-sector antenna and the multiple-sensor adaptive antenna. Beamforming, nullsteering and adaptive nullsteering, which are used in SDMA, are based on the
multiple-sensor adaptive antenna architecture and will be presented next. The steady-state solution, which is also known as Wiener solution [7], of adaptive nullsteering is then mathematically derived. In practical applications, the Wiener solution is seldom estimated directly in receivers. So, adaptive algorithms are often used to calculate this solution recursively. In this thesis, the DMI, LMS and RLS adaptive algorithms will be presented. Finally, the performance improvements of beamforming, nullsteering and adaptive nullsteering are compared in terms of received SIR and SNR.

In Chapter 3, the IS-95 channel model which is used in our simulation is presented. Large-scale fading and small-scale fading model are studied first. A correlated Rayleigh fading model, which has been implemented in our actual simulation, is presented in this chapter. Following that, a scattering model is introduced. Finally, in order to simulate realistic multipath environment, Hashemi model [22] is used to generate the power for each multipath component and will be presented in this chapter as well.

Chapter 4 presents the required background on the uplink and downlink traffic channel in the IS-95 standard [24]. In order to simulate these channels at chip level, the system frame structure and individual components of the transmitter and receiver must be understood. This components will be presented and analyzed with sufficient details.

In Chapter 5, the convergence performances of the three adaptive algorithms (DMI, LMS and RLS) in conjunction with the adaptive nullsteering antenna in the uplink and downlink traffic channel are evaluated. For simplicity, only single-cell system is considered in this thesis. These three adaptive algorithms are modified to conform to the IS-95 receiver structure. Finally, the performances of adaptive nullsteering are compared with that without adaptive antenna in terms
of the steady-state received SINR result.

In Chapter 6, we present system capacity simulation results for adaptive nullsteering, beamforming and that without smart antenna. At the beginning of this chapter, the parameters necessary for IS-95 system capacity simulation are stated. Following that, the overall simulation methodologies for both downlink and uplink are presented. A Bit-Error-Rate (BER) performance model [25], which is used in this system capacity simulation, is then discussed briefly. Finally, the system capacity simulation results are illustrated in terms of cumulative probability density graphs. Extensive system capacity performance results are presented and interpreted, including the system capacity results for the single link and multipath IS-95 system (based on the Hashemi urban environment model [22]), for the IS-95 system using adaptive nullsteering and beamforming, for the uplink and downlink and for different antenna configurations.
Chapter 2  SMART ANTENNA TECHNOLOGY

2.1 Introduction

The use of antenna technology plays an important role for the overall system capacity because of their abilities to vary the antenna gain in the azimuth direction (horizontal plane). Interference received at the antenna can be mitigated through careful design of the antenna, thus attaining a higher SINR, which in turn increases the system capacity. In this chapter, we will investigate antenna gain patterns of the most important antenna configurations in the azimuth direction. Vertical variations of antenna gain pattern are omitted for the sake of simplicity [26]. The organization of this chapter is as follows. Sections 2.2 and 2.3 present the well-known omnidirectional and 3-sectored antenna configuration respectively, which are fundamental blocks for our antenna simulations. Section 2.4 presents the adaptive antenna architecture. Adaptive antenna is usually in the form of an array of antenna elements and these antenna elements can either be omnidirectional or 3-sectored antennas. In this section, the three most important SDMA smart antenna technologies which employ this architecture, namely the beamforming, nullsteering and adaptive nullsteering technologies, are presented and compared. By controlling a parameter referred to as “weight vector” in this architecture, the same architecture can be used to deploy these three technologies. The algorithms to calculate this steady-state weight vector specifically for the adaptive nullsteering technology are also presented in this section. Finally, Section 2.5 presents the adaptive algorithms to estimate this steady-state weight vector recursively.

2.2 Omnidirectional Antennas

It is well-known that an omnidirectional antenna has a radiation pattern non-directional in azimuth direction as shown in Fig. 2.1, where the normalized gain is unity in all directions.
This kind of antenna alone does not provide any improvement on SINR because its gain pattern does not mitigate any interference. However, it is still popular because of its simplicity in its hardware implementation and is suitable to applications where mobility is a factor, such as hand-held devices etc.

![Normalized gain pattern of an omnidirectional antenna](image)

Fig. 2.1 Normalized gain pattern of an omnidirectional antenna

### 2.3 Sectored Antennas

Sectored antennas refer to those antennas that have high antenna gain in their patterns over a certain angular sector in the azimuth direction but very low gain in other directions. These antennas are also known as directional antennas and because of their nature, they can be used to mitigate interference.

With each sectored antenna covering a small sector, interference signals arriving outside the high antenna gain sector can be effectively mitigated. However, the smaller the sector each antenna covers, the more antennas are needed to cover the whole 360° circle, leading to an
increase in the complexity of the antenna structure and resources, such as the number of antenna element used. Three-sectored antenna is commonly used in cellular systems nowadays. Fig. 2.2 shows the antenna gain patterns for these antennas. They have a normalized unity gain over a 120° sector, and have an antenna gain of zero for signal arrivals outside the sector. In this thesis, ideal 3-sectored antennas are considered in the system capacity simulation.

![Figure 2.2: Normalized gain pattern of a 3-sectored antenna](image)

### 2.4 Adaptive Antennas

The name of adaptive antenna is derived from the fact that this type of antenna can modify its directional pattern adaptively in response to the arrived signal and interference strengths and directions, so as to effectively mitigate the incoming interference signals in real time and achieves a higher SINR. In the past, adaptive antennas have been considered for military applications [13] due to their abilities to suppress jamming signals and at the same time enhance the reception of desired signals. Having its root in military applications, smart antenna is making its way into the
commercial realm for narrowband, cellular and broadband wireless. In the following subsections, the structure of adaptive antenna and different criteria to optimize the received SIR, SNR and SINR in the adaptive antenna are presented. Section 2.4.1 describes the geometrical form of adaptive antenna, which is implemented in the form of an antenna array. Section 2.4.2 presents the basic system architecture of adaptive antenna. In Sections 2.4.3-2.4.5, the expressions of weight vector are derived for the case of beamforming, nullsteering and adaptive nullsteering antennas. Section 2.4.5 describes different algorithms in realizing the adaptive nullsteering antennas, including Minimum Mean Square Error (MMSE), Minimum Variance Distortionless Response (MVDR) and Maximal Signal-to-Noise Ratio (MSINR) algorithms.

2.4.1 Multiple-Sensor Antenna Array

Unlike the omnidirectional and sectored antennas, adaptive antennas consist of an array of spatially distributed antenna sensors. Antenna arrays have several advantages over a single antenna. Firstly, they can be used to enhance the received SINR by combining signals from different antenna sensors in the array coherently. Secondly, they can be used to estimate additional information about the received signal such as for example the AOA of signals and interference. Antenna array can be implemented in different geometrical ways, such as in circular form (illustrated in Fig. 2.3) or in a linear form (illustrated in Fig. 2.4). In the latter case it is referred to as an Uniform-calibrated Linear Array (ULA). Throughout this thesis, we will assume the antenna array to be of the ULA form.

With the uniform linear array consisting of $M$ sensors as illustrated in Fig. 2.4, consider a single user system with the user represented by a point source. By assuming that the source is located in far field, impinging wavefronts arriving at the antenna can be considered planar [26].
Fig. 2.3  A circular array antenna consisting of eight antenna elements
The signal $x_i(t)$ arriving at the $i$-th antenna element can be mathematically represented as a complex waveform as

$$x_i(t) = a_i(t) \exp\{j[2\pi f_c t + \phi_i(t)]\}$$

where $a_i(t)$ and $\phi_i(t)$ are the instantaneous amplitude and phase of the incoming wavefront at the $i$-th antenna element respectively, $j = \sqrt{-1}$ and $f_c$ is the carrier frequency of the signal. After amplitude normalization with reference to $a_i(t)$ and after baseband conversion, the received
signal \( x_i(t) \) at the \( i \)-th antenna element becomes

\[
x_i(t) = \exp[j\phi_i(t)]. \tag{2.2}
\]

For the sake of convenience of presentation, we represent the instantaneous values \( x_i(t) \) as \( x_i \) and \( \phi_i(t) \) as \( \phi_i \). Eq. (2.2) thus becomes

\[
x_i = \exp(j\phi_i). \tag{2.3}
\]

As the plane wave approaches the antenna array, each sensor in the array receives a phase shifted version of the signal, relative to an arbitrary physical location within the array, known as the phase centre. For the sake of simplicity, we take each phase shifted version relative to the first sensor of the array by an amount which is proportional to the perpendicular distance between the sensor and the impinging wavefront, as illustrated in Fig. 2.4. This distance, \( d_i \), where \( i = 0, 1, ..., M - 1 \) and \( M \) is the total number of antenna elements in the array, increases as the array index \( i \) increases for waves impinging from 0° to 90° and decreases for waves impinging from 0° to -90°.

Expressing the sensor separation in terms of \( \lambda \) gives

\[
\text{sensor separation} = \frac{\lambda}{k}. \tag{2.4}
\]

For every increase in distance of wavelength \( \lambda \), there is a phase change of \( 2\pi \). Therefore, the phase for the \( i \)-th antenna sensor can be expressed as
\[ \phi_i = \frac{2\pi d_i}{\lambda}. \] (2.5)

Assuming that the wavefront has an angle \( \theta \) with the antenna array, \( d_i \) can be expressed as

\[ d_i = \frac{i\lambda \sin \theta}{k}. \] (2.6)

Substituting \( d_i \) into Eq. (2.5) gives

\[ \phi_i = \frac{i2\pi \sin \theta}{k}. \] (2.7)

Combining the received signals at each antenna element in matrix form, Eq. (2.3) becomes

\[ x = \exp(j\phi) \] (2.8)

where \( x = [x_0 \ x_1 \cdots x_{M-1}]^T \) is the received signal vector and is also called the array response vector. \( \phi = [\phi_0 \ \phi_1 \cdots \phi_{M-1}]^T \) and \( T \) denotes the matrix transpose.

Alternatively, received signal \( x_i \) at the \( i \)-th antenna element may also be expressed as

\[ x_i = \exp(j2\pi i v) \] (2.9)

where \( v = (\sin \theta)/k \) is the spatial frequency across the antenna array, and is a function of the direction of arrival \( \theta \) and the sensor separation. Let us now consider the case where there are multiple users in the system, so that plane wavefronts from the \( n \)-th user are impinging the
antenna array at an angle of $\theta_n$. Assuming that signal from each user is narrowband and has the same carrier frequency $f_c$, then the combined received signal $x_i$ at the $i$-th antenna sensor is given by

$$x_i = a_0 \exp(j\phi_{i,0}) + a_1 \exp(j\phi_{i,1}) + \cdots + a_{N-1} \exp(j\phi_{i,N-1})$$

$$= \sum_{n=0}^{N-1} a_n \exp(j\phi_{i,n})$$  \hfill (2.10)

where $i = 0, 1, \ldots, M-1$, $N$ is the total number of users, $a_n$ is the amplitude of signal from the $n$-th user and $\exp(\phi_{i,n})$ is the array response component of the $n$-th user at the $i$-th antenna element. Similar to Eq. (2.7), the array response vector $\phi_{i,n}$ can be expressed as

$$\phi_{i,n} = \left(i \pi \sin \theta_n \right)/k.$$  \hfill (2.11)

Multiple spatial frequencies now exist across the antenna array due to superposition of the individual waveforms.

### 2.4.2 Adaptive Antenna Architecture

The basic system architecture of an adaptive antenna for either beamforming or null-steering applications, is illustrated in Fig. 2.5. This architecture can be mathematically represented by the following equation

$$y = w^* x$$  \hfill (2.12)

where $w = [w_0 \ldots w_{M-1}]^T$ is the adaptive weight vector and $[\cdot]^*$ represents the matrix
conjugate transpose. Signals arriving at the antenna array are multiplied by an adaptive weight vector $w$ and combined to produce an output $y$ which has better signal-to-interference ratio (SIR) or SNR.

![System architecture of adaptive antenna](image)

**Fig. 2.5** System architecture of adaptive antenna

### 2.4.3 Beamforming

Beamforming adaptive antenna is used to optimize the SNR at the receiver. This optimization can be achieved by setting the adaptive weight vector $w$ in such a way so that the main beam (maximum antenna gain) of the antenna is steered towards the direction of arrival of the desired user. Consider a signal arriving at the receiver at an angle $\theta$ with the component of the received signal vector $x$ expressed as in Eq. (2.8). To steer the beam towards the desired user at an angle
\( \alpha \), we can simply set

\[
    w_i = \exp(j\chi_i)
\]

(2.13)

where

\[
    \chi_i = (-i2\pi\sin\alpha)/k.
\]

(2.14)

The processed output \( y \) after the weighting operation is then given by Eq. (2.12). In Fig. 2.5, when each \( w_i \) is multiplied with the corresponding \( x_i \) given \( \alpha = 0 \), their phases in the array response vectors \( \phi_i \) and \( \chi_i \) cancel one another out. The products \( w_i^*x_i \) from the different antenna elements when added together give a scalar value of \( M \) at the desired user AOA. In other words, the desired signal phases are aligned coherently in each sensor and combined. We have simulated a beamforming system with 3 users using MATLAB. The signals from these users arrive at the antenna array at angles 20°, 30° and 50°. The antenna elements are assumed to be separated by a distance of \( \lambda/2 \). The antenna pattern is steered to each of these users. The steered angle \( \alpha \) of the antenna pattern is set by substituting the corresponding angle into Eq. (2.14). By using Eqs. (2.8), (2.12) and (2.13), the output \( y \) for each user is plotted in Fig. 2.6. In this figure, \( \theta \) is scanned from \(-180^\circ\) to \(180^\circ\). The normalized maximum antenna gain is steered at each of the AOA of the users at 20°, 30° and 50°. The SNR is optimized with this beamforming antenna pattern.

When multiple signals are illuminating the array, the weight vector \( w \) in Eq. (2.12) can be expressed in a 2-dimensional matrix form as
where $\chi_{m,i} = (-i2\pi \sin \alpha_m)/k$ with $\alpha_m$ is the angle steered to the $m$-th desired user at the $i$-th antenna array sensor.

Fig. 2.6  Examples of normalized beamforming antenna pattern with maximum antenna gain steered to the AOA of each user at $20^\circ$, $30^\circ$ and $50^\circ$
Matrix $x$ in Eq. (2.12) thus becomes

$$x = \begin{bmatrix}
    a_0 \exp(j\phi_{0,0}) + a_1 \exp(j\phi_{0,1}) + \cdots + a_{N-1} \exp(j\phi_{0,N-1}) \\
    a_0 \exp(j\phi_{1,0}) + a_1 \exp(j\phi_{1,1}) + \cdots + a_{N-1} \exp(j\phi_{1,N-1}) \\
    \vdots \\
    a_0 \exp(j\phi_{M-1,0}) + a_1 \exp(j\phi_{M-1,1}) + \cdots + a_{N-1} \exp(j\phi_{M-1,N-1})
\end{bmatrix} \quad (2.16)$$

where signals from different users are superimposed to each other in each antenna sensor.

### 2.4.4 Nullsteering

It is clear from Fig. 2.6 that the array patterns overlap so that the processed signal along each of the directions of arrival contains some interferences from the other desired signals. Hence, although beamforming optimizes the received SNR, the SIR may not be high enough for reliable communication. In this case, nullsteering is used to steer the nulls (zero or near-zero antenna gain) in the antenna gain pattern towards the interfering sources to obtain satisfactory SIR. Unlike beamforming, which requires information such as AOA and average power of desired user only, nullsteering requires similar information from the interferers as well.

In general, the processed signals $y_0, y_1, \cdots, y_{N-1}$ for $N$ steered angles $\alpha_0, \alpha_1, \cdots, \alpha_{N-1}$ when expressed in matrix form

$$\begin{bmatrix}
    y_0 \\
    y_1 \\
    \vdots \\
    y_{N-1}
\end{bmatrix} = \begin{bmatrix}
    \gamma_{0,0}a_0 + \gamma_{0,1}a_1 + \cdots + \gamma_{0,N-1}a_{N-1} \\
    \gamma_{1,0}a_0 + \gamma_{1,1}a_1 + \cdots + \gamma_{1,N-1}a_{N-1} \\
    \vdots \\
    \gamma_{N-1,0}a_0 + \gamma_{N-1,1}a_1 + \cdots + \gamma_{N-1,N-1}a_{N-1}
\end{bmatrix} \quad (2.17)$$

Simplifying Eq. (2.17), yields
or expressed in matrix form,

\[ \mathbf{y} = \mathbf{\Upsilon} \mathbf{a} \]  

(2.19)

where \( \gamma_{i,n} \) and \( a_i \) are the matrix component with the angle steered to the desired \( n \)-th user at the \( i \)-th antenna element and the antenna gain of the \( i \)-th user respectively and can be presented as

\[
\gamma_{i,n} = \sum_{n=0}^{N-1} \exp(-nj\alpha_i)\exp(nj\alpha_n). 
\]  

(2.20)

The \( \mathbf{\Upsilon} \) matrix represents the matrix of complex weights which can be used to steer beams to each individual source illuminating the array. To perform nullsteering, the processed signal vector \( \mathbf{y} \) may be expressed as

\[ \mathbf{y} = \mathbf{w}^* \mathbf{x} = \mathbf{\Upsilon} \mathbf{a}. \]  

(2.21)

Now, multiplying both sides of Eq. (2.21) by \( \mathbf{\Upsilon}^{-1} \) modifies the processed signals so that

\[ \mathbf{\Upsilon}^{-1} \mathbf{y} = \mathbf{\Upsilon}^{-1} \mathbf{w}^* \mathbf{x} = \mathbf{\Upsilon}^{-1} \mathbf{\Upsilon} \mathbf{a} = \mathbf{a}. \]  

(2.22)

This yields the desired received signal vector with no interference at the directions of arrival. From Eq. (2.22), it is evident that the new weight vector can be described by \( \mathbf{\Upsilon}^{-1} \mathbf{w}^* \) so
that the array patterns with nulls steered to coincide with each direction of arrival form the entries of the vector $\mathbf{Y}^{-1}\mathbf{w}^*\mathbf{x}$. With this new weight vector, the new output $y$ in Fig. 2.5 can be expressed as

$$y = (\mathbf{Y}^{-1}\mathbf{w}^*)\mathbf{x}.$$  \hspace{1cm} (2.23)

For example, let us consider a system with 3 users and the receiver is required to suppress the interferers’ signals using nullsteering. The signal from each user arrives at the antenna array at angles $20^\circ$, $30^\circ$ and $50^\circ$. The output $y$ for each user is calculated using Eq. (2.23), normalized and plotted in Fig. 2.7. As shown in this figure, for example, nulls are placed at $30^\circ$ and $50^\circ$ (which are the interferers’ AOA) positions of the antenna pattern when received signal from the desired user at $20^\circ$. It may seem that nullsteering is ideal for suppressing interferences at first glance because the nulls in the antenna pattern are steered towards the AOAs of the interferers. Theoretically, infinite SIR will result because the interferences are completely suppressed at the null positions of the antenna pattern. However, in reality due to the presence of thermal noise in antenna sensors, the SIR will be finite. Moreover, unlike beamforming, the maximum antenna gain of nullsteering antenna pattern does not necessarily steer towards the desired user. In addition, since it can only allocate nulls to a limited number of interferers which is equal to $M - 1$ \cite{2}, no null will be available for the excess users and hence it cannot be used with system which has many users.

2.4.5 Adaptive Nullsteering

Adaptive nullsteering combines the advantage of beamforming and nullsteering by using an adaptive weight vector which minimizes the Mean Square Error (MSE), maximizes the SINR
or minimizes the variance of noise power of the receiving signal as a whole. In the following sections, we will introduce three methods which are used to suppress interference signals, namely the Minimum Mean Square Error (MMSE) [13], Maximum Signal-to-Interference-plus-Noise Ratio (MSINR) [13] and Minimum Variance Distortionless Response (MVDR) [46] algorithms.

2.4.5.1 MMSE Algorithm

As inferred from the name, MMSE algorithm estimates the weight vector by minimizing the mean square error between a locally generated reference and weighted output. As illustrated in Fig. 2.8, the received signals arriving at the antenna array are multiplied by the adaptive weight vector \( w \) and are linearly combined.

![Figure 2.7](image-url)  

**Fig. 2.7** Examples of normalized nullsteering antenna Pattern with the antenna pattern optimized for users at 20°, 30° and 50°. For example, for the signal of the desired user arriving at 20°, the nulls are placed at 30° and 50° in the antenna pattern.
The MSE $\rho$ between the output $y$ and the desired response $y_d$ is given by

$$\rho = E[|e|^2] = E[|y_d - y|^2] = E[|y_d - w^*x|^2]$$

(2.24)

where $E[\ ]$ denotes the expected value. $\rho$ is fed back for adjusting the adaptive weight vector $w$.

Eq. (2.24) can be rewritten as

$$\rho = E[(y_d - w^*x)(y_d^*-x^*w)]
= y_d^2 - w^*E[xy_d^*] - E[y_d x^*]w + w^*E[x x^*]w .$$

(2.25)

![MMSE adaptive nullsteering block diagram](image)

Fig. 2.8 MMSE adaptive nullsteering block diagram
In a more compact form, Eq. (2.25) can be expressed as

\[ \rho = y_d^2 - w^* r_{xd} - r_{xd}^* w + w^* R_{xx} w \]  

(2.26)

with

\[ r_{xd} = E[x y_d^*] \]  

(2.27)

where \( r_{xd} \) is the cross-covariance vector between the received signal vector \( x \) and the desired response \( y_d \). The autocovariance matrix of the received data vector is given by

\[ R_{xx} = E[xx^*]. \]  

(2.28)

An unique solution for the weight vector \( w \), which gives the minimum \( \rho \) in Eq. (2.26), exists only if the quadratic form \( w^* R_{xx} w > 0 \) for every non-zero complex vector \( w \), i.e. when matrix \( R_{xx} \) is positive definite [28]. It is also known that \( R_{xx} \) is Hermitian and non-negative definite [28]. Also, in practice, the existence of an Additive White Gaussian Noise (AWGN) is often assumed in the received signal which leads to positive power value in the diagonals of \( R_{xx} \). Therefore, based on the above arguments, the outcoming autocovariance matrix \( R_{xx} \) can be assumed to be always positive definite.

To minimize the MSE \( \rho \), let us consider the gradient vector of \( \rho \) with respect to \( w \) and setting it to zero, i.e.

\[ \nabla \rho = 2 R_{xx} w - 2r_{xd} = 0. \]  

(2.29)
Since the matrix $R_{xx}$ is positive definite, its inverse $R_{xx}^{-1}$ exists. Solving Eq. (2.29), the adaptive weight vector that minimizes the MSE is given by

$$w_{MMSE} = R_{xx}^{-1}r_{xd}. \quad (2.30)$$

### 2.4.5.2 MSINR Algorithm

The MSINR algorithm estimates a weight vector which optimizes the SINR. Using the general block diagram in Fig. 2.5, and by taking into account the interference and noise which could be present in the received signal, the total output signal after weighting and combining is

$$y = w^*x = w^*[s + (i + n)] = y_s + y_{NI} \quad (2.31)$$

where $s = a\chi$ is the desired received signal column vector, $i = [i_0i_1\ldots i_{M-1}]^T$ is the interference signal column vector and $n = [n_0n_1\ldots n_{M-1}]^T$ is the noise column vector. $y_s$ is the output for the weighted desired signal and $y_{NI}$ is the output for the weighted noise-plus-interference signal. To estimate the SINR, we need to calculate the weighted signal power $P_{y_s}$ and the weighted noise-plus-interference power $P_{y_{NI}}$. The signal power $P_{y_s}$ is given by

$$P_{y_s} = E[|y_s|^2] = w^*E[ss^*]w = w^*R_{ss}w \quad (2.32)$$

where $R_{ss}$ is the autocovariance matrix of desired signal after weighting and

$$P_{y_{NI}} = E[|y_{NI}|^2] = w^*E[i + n|^2]w = w^*R_{NI}w \quad (2.33)$$
where $R_{NI}$ is the autocovariance matrix of noise-plus-interference.

Therefore, the SINR can be expressed as

$$SINR = \frac{P_y}{P_{yi}} = \frac{w^* R_{ss} w}{w^* R_{NI} w}.$$  \hspace{1cm} (2.34)

In order to calculate the weight vector $w$ which gives minimum SINR, we take the derivatives of Eq. (2.34) with respect to $w$. By setting it to zero, the result becomes

$$R_{ss} w = \frac{w^* R_{ss} w}{w^* R_{NI} w} R_{NI} w$$  \hspace{1cm} (2.35)

which is a generalized eigenproblem with the eigenvalue $\zeta = (w^* R_{ss} w)/(w^* R_{NI} w)$ and is bounded by the minimum and maximum value of $R_{NI}^{-1} R_{ss}$. The maximum eigenvalue $\zeta_{max}$ satisfies the equation

$$R_{NI}^{-1} R_{ss} w = \zeta_{max} w$$  \hspace{1cm} (2.36)

and is the optimum value of SINR. Corresponding to this value, there is an unique eigenvector $w_{MSINR}$, which represents the optimum weight vector. Therefore,

$$w_{MSINR} = (R_{NI}^{-1} R_{ss} w)/(SINR_{min})$$  \hspace{1cm} (2.37)

where $SINR_{min}$ is the minimum value of SINR. Since $s = a\chi$, therefore
where \( \Theta \) is a complex scalar and is given by

\[
\Theta = \frac{E[a^2]}{SINR_{\text{min}}} \chi^* w_{\text{MSINR}}.
\]  

### 2.4.5.3 MVDR Algorithm

If the desired signal amplitude and its direction are both unknown, one way to ensuring a good signal reception is to constrain the gain of the main beam in the antenna pattern so that no power is lost from the signal and at the same time with the noise variance is minimized. The MVDR algorithm is used to estimate a weight vector in such a way. The receiver output \( y \) is the same as in Eq. (2.31). To ensure the desired signal is passed with a specific gain and phase, a constraint may be used so that the response of the beamformer to the desired signal becomes

\[
w^* \chi = g
\]  

where \( g \) is a scalar.

Minimization of the interference in the output signal \( y \) is accomplished by choosing the weight vector \( w \) to minimize the variance of the output power signal

\[
Var[y] = w^* R_{xx} w = w^* R_{ss} w + w^* R_{NI} w
\]  

where \( Var[\cdot] \) denotes the variance of the signal. Eq. (2.41) is subject to the constraint defined in Eq. (2.40). By using the Lagrange method, we have
\[ \nabla_w \left( \frac{1}{2} \text{Var}[y] + \gamma [g - w^* \chi] \right) = R_{xx} w - \gamma \chi \]  

(2.42)

where \( \gamma \) is the Lagrange multiplier [28] and \( \nabla_w \) denotes the gradient vector with respect to \( w \).

By setting the right hand side of Eq. (2.42) to zero, it follows that

\[ w_{MVDR} = \gamma R_{xx}^{-1} \chi. \]  

(2.43)

Substituting Eq. (2.43) into Eq. (2.40) gives the value of \( \gamma \)

\[ \gamma = \frac{g}{\chi^* R_{xx}^{-1} \chi}. \]  

(2.44)

When \( g = 1 \), the response of the beamformer is often called the MVDR beamformer.

### 2.4.5.4 Equivalence of Steady-State Weight Vector Estimation Algorithms

In the previous sections, we have presented three algorithms in calculating the optimal steady-state weight vector based on different criteria. In this section, we are going to show that all three steady-state weight vectors obtained from these three algorithms are equivalent.

Recalling that \( s = a \chi \), \( R_{xx} \) can be expressed as

\[ R_{xx} = R_{ss} + R_{NI} = a^2 \chi \chi^* + R_{NI}. \]  

(2.45)

Applying the matrix inversion lemma [28] to \( R_{xx} \), yields
\[ R_{xx}^{-1} = R_{NI}^{-1} \frac{a^2 R_{NI}^{-1} \chi \star R_{NI}^{-1}}{1 + a^2 \chi^*(t) R_{NI}^{-1} \chi(t)} = \frac{1}{1 + a^2 \chi^* R_{NI}^{-1} \chi} R_{NI}^{-1} = \Gamma R_{NI}^{-1} \]  

(2.46)

where \( \Gamma \) is a scalar.

Since \( R_{xx}^{-1} \) can be expressed in terms of \( R_{NI}^{-1} \) within a constant scale factor \( \Gamma \), therefore, within this constant scale factor, the optimum weight vector estimation equations for MMSE, MSINR and MVDR criteria are equivalent with each other and they converge to the same steady-state Wiener solution [13]. Since this scale factor only affects the overall amplitude of the antenna pattern but not the actual shape of the pattern, any arbitrary value could be chosen. Thus, for simplicity, this scale factor is chosen to be unity. Depending upon the availability of the desired signal strength, noise-plus-interference strength or AOA of desired user, Eqs. (2.30), (2.38) or (2.43) can be used to estimate the steady-state weight vector. Since all the three algorithms are equivalent, using any one of them will create an antenna pattern which maximizes the received SINR.

As an example and similar to that for beamforming and nullsteering, let us consider again an adaptive nullsteering system with 3 users and with their signals arriving at the antenna array at angles 20°, 30° and 50°. Eq. (2.38) is used to estimate the weight vector. The output \( y \) is plotted in Fig. 2.9 using Eq. (2.12). In this figure, for example, the received SINR for the desired user at 20° is maximized by placing the nulls at 30° and 50° location of the antenna pattern. However, as the number of users increases and exceeds the number of nulls provided by the pattern, the nulls are not necessarily steered to the interferers’ AOA as in the nullsteering case.

In order to compare the performance between beamforming, nullsteering and adaptive
nullsteering, the SIR and SNR data for a system with 3 users are taken from Figs. 2.6, 2.7 and 2.9 and are summarized in Tables 2.1 and 2.2. Another system with 5 users is also simulated for the case of beamforming, nullsteering and adaptive nullsteering with their SIR and SNR data presented in Tables 2.3 and 2.4. As shown in Table 2.2 and 2.4, beamforming optimizes the SNR better than nullsteering and adaptive nullsteering. However, since it does not take into account the statistics of interferers, it is inferior to nullsteering and adaptive nullsteering in the SIR sense, as illustrated in Table 2.1. In Fig. 2.7, nullsteering allocates nulls at angles 20°, 30° and 50° so that the incoming interference at these directions are nullified, thus yielding a large SIR as shown in Table 2.1. On the other hand, for beamforming, a beam is steered towards the desired user’s direction, but the antenna pattern does not take into account the interferers’ directions, yielding a poorer SIR than nullsteering.

From the above results, it may seem that nullsteering is the best among the three at the first glance. However, since it can only allocate nulls to a limited number of interferers’ AOA which is equal to $M - 1$ as mentioned before, when the number of user is larger than $M - 1$, no nulls will be available for the excess users. Thus, for a system with many users (i.e. $> M - 1$), adaptive nullsteering always performs better because it forms an antenna pattern which optimizes the SIR with values as shown in Table 2.3, giving the highest system capacity among the three methods.

### 2.5 Recursive Approach for Real Time Adaptive Nullsteering

In the previous section, we have derived optimum weight vector equations which maximize the SINR. In reality, these equations are not used directly but instead adaptive approaches are used to estimate the weight vectors based upon these equations. There are two important reasons for this choice. Firstly, direct calculation of this weight vector is too computa-
tional intensive because it involves matrix inversion operation [13]. As well-known, although adaptive approaches cannot be used to estimate the weight vector instantly, recursive application of these approaches will eventually converge to the steady-state optimum weight vector solution.

Fig. 2.9 Examples of normalized adaptive nullsteering antenna pattern with the antenna pattern optimized for each of the users at 20°, 30° and 50°. For example, for the signal of the desired user arriving at 20°, the nulls are placed at 30° and 50° in the antenna pattern. Noise power = 0.1W
Table 2.1 SIR comparison between beamforming, nullsteering and adaptive nullsteering with 3 users. INF represents very large number\(^1\).

<table>
<thead>
<tr>
<th>Desired User AOA</th>
<th>Beamforming (dB)</th>
<th>Nullsteering (dB)</th>
<th>MSINR Nullsteering (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20°</td>
<td>1.19</td>
<td>INF</td>
<td>89.04</td>
</tr>
<tr>
<td>30°</td>
<td>-0.42</td>
<td>INF</td>
<td>88.47</td>
</tr>
<tr>
<td>50°</td>
<td>3.87</td>
<td>INF</td>
<td>92.18</td>
</tr>
</tbody>
</table>

Table 2.2 SNR comparison between beamforming, nullsteering and adaptive nullsteering with 3 users, noise Power = 0.1W

<table>
<thead>
<tr>
<th>Desired User AOA</th>
<th>Beamforming (dB)</th>
<th>Nullsteering (dB)</th>
<th>MSINR Nullsteering (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20°</td>
<td>10.00</td>
<td>-0.34</td>
<td>-0.34</td>
</tr>
<tr>
<td>30°</td>
<td>10.00</td>
<td>-1.95</td>
<td>-1.95</td>
</tr>
<tr>
<td>50°</td>
<td>10.00</td>
<td>3.23</td>
<td>3.23</td>
</tr>
</tbody>
</table>

Table 2.3 SIR comparison between beamforming, nullsteering and adaptive with 5 users

<table>
<thead>
<tr>
<th>Desired User AOA</th>
<th>Beamforming (dB)</th>
<th>Nullsteering (dB)</th>
<th>MSINR Nullsteering (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20°</td>
<td>0.73</td>
<td>20.48</td>
<td>22.87</td>
</tr>
<tr>
<td>30°</td>
<td>-0.51</td>
<td>13.00</td>
<td>15.28</td>
</tr>
<tr>
<td>50°</td>
<td>-2.09</td>
<td>7.31</td>
<td>9.23</td>
</tr>
<tr>
<td>80°</td>
<td>-1.93</td>
<td>3.05</td>
<td>4.00</td>
</tr>
<tr>
<td>110°</td>
<td>-2.32</td>
<td>-20.48</td>
<td>-1.31</td>
</tr>
</tbody>
</table>

Table 2.4 SNR comparison between beamforming, nullsteering and adaptive nullsteering with 5 users, noise Power = 0.1W

<table>
<thead>
<tr>
<th>Desired User AOA</th>
<th>Beamforming (dB)</th>
<th>Nullsteering (dB)</th>
<th>MSINR Nullsteering (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20°</td>
<td>10.00</td>
<td>-6.53</td>
<td>-6.29</td>
</tr>
<tr>
<td>30°</td>
<td>10.00</td>
<td>-10.86</td>
<td>-10.70</td>
</tr>
<tr>
<td>50°</td>
<td>10.00</td>
<td>-8.95</td>
<td>-8.99</td>
</tr>
<tr>
<td>80°</td>
<td>10.00</td>
<td>-3.12</td>
<td>-8.36</td>
</tr>
<tr>
<td>110°</td>
<td>10.00</td>
<td>-27.01</td>
<td>-4.58</td>
</tr>
</tbody>
</table>

\(^1\) A very large SIR is obtained because the interference is almost nullified.
Secondly, as the communication environment is continuously changing, parameters such as AOA and signal amplitude in the weight vector equation are changing as well. Therefore, in order to adapt to the environment in "almost" real time, adaptive approaches must be used. In this section, three important adaptive algorithms, namely the DMI [13][14][49], LMS [13][14][15][49] and RLS [14][15] algorithms will be presented. They are selected as the adaptive algorithms in this thesis firstly because of the simplicity. Secondly, these algorithms are well studied and understood.

2.5.1 Direct Matrix Inversion (DMI)

DMI is the fastest algorithm [13] among the three which enables the fastest adaptation to the steady-state optimum adaptive weight vector by directly calculating each of the parameters in either Eqs. (2.30), (2.38) or (2.43). As it can be noted from these equations, the DMI algorithm requires either knowledge of the noise-plus-interference autocovariance matrix \( R_{NI} \), the incoming signal autocovariance matrix \( R_{xx} \), the cross-corvariance matrix of incoming and desired signal \( r_{xd} \) or the array response vector of desired signal \( \chi \). The array response vector \( \chi \) can be calculated given the AOA, which can be estimated from algorithms such as ESPRIT [18], MUSIC [17] or code filtering [27]. However, second order statistics for the above autocovariance or cross-covariance matrices are usually unavailable. As a result, ergodicity is often assumed and the ensemble average is taken to be equal to the time average of the samples, giving the sample autocovariance matrix \( \hat{R}_{NI} \), \( \hat{R}_{xx} \) or the sample cross-covariance matrix \( \hat{r}_{xd} \). Since, in general, direct estimation of these matrices requires significant computational efforts, the whole process can be further simplified by using the exponentially-weighted method to update the matrices in
each cycle [13]. In this case, the sample autocovariance matrix \( \hat{R}_{xx} \) is given by

\[
\hat{R}_{xx}(k) = \sum_{n=0}^{k-1} \alpha_{DMI}^{k-n-1} x(n)x^*(n)
\]

or in a recursive form,

\[
\hat{R}_{xx}(k) = \alpha_{DMI} \hat{R}_{xx}(k-1) + x(k)x^*(k).
\] (2.48)

A similar expression can be obtained for the sample noise-plus-interference autocovariance matrix \( \hat{R}_{NI} \)

\[
\hat{R}_{NI}(k) = \alpha_{DMI} \hat{R}_{NI}(k-1) + NI(k)NI^*(k)
\]

where \( NI(k) \) is the noise-plus-interference signal at time index \( k \). For the sample cross-covariance matrix \( \hat{r}_{xd} \),

\[
\hat{r}_{xd}(k) = \alpha_{DMI} \hat{r}_{xd}(k-1) + x(k)d(k).
\] (2.50)

In the above equations, \( \alpha_{DMI} \) is the so-called "forgetting factor" and it takes values \( 0 < \alpha_{DMI} < 1 \) [28]. The larger the \( \alpha_{DMI} \), the higher the effect of past matrix data has on the present covariance matrix and vice versa.
2.5.2 Least Mean Square Error (LMS)

As well-known, the advantage of LMS algorithm lies in its simplicity as it does not require measurements of the pertinent correlation functions, nor does it require computational intensive matrix inversion [15]. The criterion of LMS algorithm is to minimize the MSE between the reference $y_d$ and the actual output $y$ as shown in Fig. 2.10. To update the adaptive weight vector in each time index $k$, changes in the weight vector are made in the direction given by an estimated gradient vector.

The MSE at time index $k$ is

$$\rho(k) = E[|y_d(k) - y(k)|^2] = E[|y_d(k) - w(k)^*x(k)|^2] = E[\varepsilon(k)^2]. \quad (2.51)$$

Differentiating the MSE $\rho(k)$ with respect to the weight vector $w(k)$ yields the estimated gradient vector

$$\nabla_w(k)\rho(k) = -2[y_d(k) - w^*(k)x(k)]x(k). \quad (2.52)$$
The LMS algorithm then updates the weight vector at each time index $k$ using Eq. (2.53), with the change in weight vector made in the same direction as the estimated gradient vector. Hence, the updated weight vector can be expressed as

$$w(k+1) = w(k) + \mu \hat{\nabla}_{w(k)} p(k)$$

$$= w(k) - 2\mu [y_d(k) - w^*(k)x(k)]x(k)$$  \hspace{1cm} (2.53)$$

where $\mu$ is a scalar and affects the stability and the speed of convergence to the mean value of the weight vector. The larger the $\mu$ is, the faster the convergence is. However, care should be taken in order to prevent overshooting into the instability region. Conversely, the smaller is the $\mu$, the slower is the convergence rate. To guarantee convergence, $\mu$ should be set such that
\[
\frac{1}{\zeta_{\text{max}}} \leq \mu < 0 \quad (2.54)
\]

where \( \zeta_{\text{max}} \) is the maximum eigenvalue of \( R_{xx} \) \[13][14][15]\. Hence, \( \zeta_{\text{max}} \) satisfies the inequality,

\[
\zeta_{\text{max}} \leq \text{trace}[R_{xx}] \quad (2.55)
\]

where

\[
\text{trace}[R_{xx}] = E[x^*(k)x(k)] = \sum_{i=1}^{M} E[x_i^2]. \quad (2.56)
\]

is the total input power.

2.5.3 Recursive Least Square (RLS)

The convergence rate of the gradient-based LMS algorithm is very slow, especially when the eigenvalues of the input covariance matrix \( R_{xx} \) have a very large eigenvalue spread. One way to improve the convergence speed without much increase in hardware complexity is to use the RLS algorithm. This algorithm is based on a least square approach, as opposed to the statistical approach used in the LMS algorithm. That is, rapid convergence relies on error measures expressed in terms of a time average of the actual received signal instead of a statistical average.

We have shown that the optimum adaptive weight vector can be expressed as in Eq. (2.30). To estimate the sample input covariance matrix \( \hat{R}_{xx} \) or the sample cross-covariance matrix \( \hat{r}_{xd} \) in this equation recursively, the exponentially-weighted approach is used as shown in Eqs. (2.48)
and (2.50).

To calculate the inverse of \( \hat{R}_{xx} \) recursively, the matrix inverse lemma [28] is applied to Eq. (2.48). The inverse of the input covariance matrix \( \hat{R}_{xx}^{-1} \) can now be expressed as

\[
\hat{R}_{xx}^{-1}(k) = \frac{1}{\alpha_{RLS}} \left[ R_{xx}^{-1}(k-1) - \frac{R_{xx}^{-1}(k-1)x(k)x^*(k)R_{xx}^{-1}(k-1)}{\alpha_{RLS} + x^*(k)R_{xx}^{-1}(k-1)x(k)} \right]
\]

\[
= \frac{1}{\alpha_{RLS}} [R_{xx}^{-1}(k-1) - q(k)x^*(k)R_{xx}^{-1}(k-1)]
\]

(2.57)

where

\[
q(k) = \frac{\hat{R}_{xx}^{-1}(k-1)x(k)}{\alpha_{RLS} + x^*(k)R_{xx}^{-1}(k-1)x(k)}.
\]

(2.58)

Substituting Eqs. (2.57) and (2.50) into Eq. (2.30), the optimized weight vector can be obtained as follows:
\[ w(k+1) = R_{xx}^{-1}(k)r_{xd}(k) \]

\[ = \frac{1}{\alpha_{RLS}}[R_{xx}^{-1}(k-1) - q(k)x^*(k)R_{xx}^{-1}(k-1)]\alpha_{RLS}r_{xd}(k-1) + x(k)d(k)] \]

\[ = R_{xx}^{-1}(k-1)r_{xd}(k-1) - q(k)x^*(k)R_{xx}^{-1}(k-1)r_{xd}(k-1) \]

\[ + \frac{1}{\alpha_{RLS}}R_{xx}^{-1}(k-1)x(k)d(k) - \frac{1}{\alpha_{RLS}}q(k)x^*(k)R_{xx}^{-1}(k-1)x(k)d(k) \]

\[ = w(k) - q(k)x^*(k)w(k) + \frac{1}{\alpha_{RLS}}[\alpha_{RLS} + x^*(k)\hat{R}_{xx}^{-1}(k-1)x(k)]q(k)d(k) \]

\[ - \frac{1}{\alpha_{RLS}}q(k)x^*(k)\hat{R}_{xx}^{-1}(k-1)x(k)d(k) \]

\[ = w(k) - q(k)[d(k) - x^*(k)w(k)] \]

\[ = w(k) - q(k)[d(k) - w^*(k)x(k)]. \quad (2.59) \]

In the above equations, \( \alpha_{RLS} \) is the weighting coefficient which governs the performance of the adaptive processor. The value of \( \alpha_{RLS} \) has no influence on the rate of convergence, but determines the tracking ability of the adaptive processor. The smaller the \( \alpha_{RLS} \) is, the better the tracking ability of the adaptive processor becomes. However, if \( \alpha_{RLS} \) is too small, it will lead to instability of the algorithm. To ensure stability, \( \alpha_{RLS} \) is chosen to be between 0 and 1.

### 2.6 Conclusions

In this chapter, we have presented the basic structure for beamforming, nullsteering and adaptive nullsteering antennas. Beamforming can optimize the SNR by steering the beam towards the desired user and nullsteering can optimize the SIR by steering the nulls towards the interferers. However, beamforming does not take into account the statistics of the interferers and
nullsteering can only allocate a limited number of nulls. Adaptive nullsteering antenna overcomes these problems by creating an antenna pattern which optimizes the received SINR. The basic smart antenna architecture can be used for beamforming, nullsteering and adaptive nullsteering by changing the weight vector. We have derived the weight vector steady-state expressions for these three kinds of antennas. Specifically, MMSE, MVDR and MSINR algorithms can be used to estimate the steady-state adaptive nullsteering weight vector. These three algorithms are equivalent in the sense that the same antenna patterns are created. Recursive approaches such as DMI, LMS and RLS can be used to calculate this adaptive nullsteering weight vector in real time. DMI enables the weight vector to converge quickly to its steady-state value with the expense of complicated hardware. LMS is the simplest in hardware implementation, however, it has the slowest convergence rate. RLS is the best if we take into account the convergence rate and hardware complexity.
Chapter 3 CHANNEL MODELLING

3.1 Introduction

In order to simulate the convergence performance of the adaptive algorithms and to investigate the effects these algorithms have on the cellular system capacity, the channel in which the signals transmitted must be appropriately modelled. The transmitted signal may undergo different delays and distortions in the communication channel due to large-scale fading, small-scale fading and scattering before arriving at the receiver. This chapter will present the channel models which have been used in this thesis. Its organization is as follows. After this introduction, Section 3.2 presents the large-scale fading model. Section 3.3 presents the small-scale fading model and finally, Section 3.4 presents the scattering model.

3.2 Large-Scale Fading

We will describe the large-scale fading model in this section. Large-scale fading models are used to predict the mean signal strength for an arbitrary transmitter-receiver separation distance and is very useful in estimating the radio coverage area of a transmitter. They are called large-scale because they characterize signal strength over large transmitter-receiver distances which are usually several hundreds or thousand of meters. The two major factors contributing to this fading are propagation loss and shadowing.

3.2.1 Propagation Loss

The power of transmitted signal attenuates in the propagating medium and is proportional to attenuation factor $\kappa = d^{-r}$, where $d$ is the distance between transmitter and receiver, and $r$ is the path loss exponent [29]. The larger is the path loss exponent, the greater is the attenuation of
the received signal power. A typical value of $r = 4$ is assumed in this thesis which is suitable for shadowed urban cellular radio environment (see for example [29]).

The attenuation on the received signal power is calculated by multiplying the signal power with the attenuation factor. In order to model the signal envelope amplitude attenuation, the signal amplitude should be multiplied by $\sqrt{\kappa}$ instead. For realistic large-scale path loss simulations, however, the actual terrain profile of a particular area needs to be taken into account for estimating path loss. Such models are based on a systematic interpretation of measurement data obtained in the service area. In this thesis, the Hata-Okumura model is used to generate realistic path loss. This model is an empirical formulation of the graphical path loss data provided by Okumura [29], and is valid for the RF range from 150 MHz to 1.5 GHz. Hata presented the urban area propagation loss as a standard formula and supplied correction equations for application to other frequency bands and propagation environments. Simulations are performed for 4 different areas in this thesis, namely downtown San Francisco, downtown Oakland, downtown Berkeley and residential Berkeley. These four areas characterize different levels of urbanizations. Downtown San Francisco represents a large city, downtown Oakland represents a small to medium sized city, downtown Berkeley represents a suburban area and residential Berkeley represents an open rural area.

The standard median path loss $L$ in dB in urban areas such as downtown San Francisco and downtown Oakland is given by [29]

$$L(\text{urban})(dB) = 69.55 + 26.16 \log f_c - 13.82 \log h_{te} - a(h_{re})$$

$$+ (44.9 - 6.55 \log h_{te}) \log d$$

(3.1)
where $f_c$ is the carrier frequency, $h_{te}$ is the effective basestation antenna height in meters, $h_{re}$ is the effective mobile antenna height in meters, $d$ is the transmitter-receiver separation distance in km, and $a(h_{re})$ is the correction factor for effective mobile antenna height which is a function of the size of the coverage area.

The correction factor for downtown Oakland is given by [29]

$$a(h_{re}) = (1.1 \log f_c - 0.7)h_{re} - (1.56 \log f_c - 0.8) \text{ dB}$$

(3.2)

and that for downtown San Francisco is given by [29]

$$a(h_{re}) = 3.2(\log 11.75 h_{re})^2 - 4.97 \text{ dB}$$

(3.3)

The standard median path loss $L$ in dB in suburban areas such as downtown Berkeley is given by [29]

$$L(dB) = L(urban) - 2[\log (f_c/28)]^2 - 5.4$$

(3.4)

and that for open rural area such as residential Berkeley is given by [29]

$$L(dB) = L(urban) - 4.78(\log f_c)^2 - 18.33 \log f_c - 40.98.$$  

(3.5)

### 3.2.2 Lognormal Shadowing

The path loss model does not consider the fact that the surrounding environmental clutter may be vastly different at two different locations with the same transmitter-receiver distance separation. To account for the difference, the shadowing model is employed. Shadowing occurs when the signal paths between users and basestations are attenuated by obstacles in between, such
as trees, buildings, cars etc. This shadowing phenomenon is lognormal because when the mobile users pass through random shadowing areas, the measured signal level for a specific mobile-basestation pair has a Gaussian distribution about the distance-dependent pathloss mean, with the measured signal levels in dB. In this thesis, the shadowing effect is assumed to be a lognormal random variable with a standard deviation of 8 dB [1].

### 3.3 Small-Scale Fading

While large-scale fading model characterizes signal strength over large transmitter-receiver distances, small-scale fading model characterizes the rapid fluctuations of the received signal strength over very short travel distances (a few wavelengths) or short time durations (on the order of seconds). This kind of fading is caused by interference between two or more versions of the transmitted signal which arrive at the receiver at slightly different times $\tau$ because of multiple reflections as illustrated in Fig. 3.1. These multipath waves combine at the receiver antenna resulting in constructive or destructive interferences. The resultant signal fluctuates widely in amplitude and phase and depends on the distribution of the intensity, relative propagation time of the waves and the bandwidth of the transmitted signal. These fading effects can be classified into four categories, namely flat fading, frequency selective fading, fast fading and slow fading [30].

Flat fading occurs when the mobile radio channel has a constant gain and linear phase response over a bandwidth which is greater than the bandwidth of the transmitted signal. Conversely, if the channel has a constant gain and linear phase response over a bandwidth that is smaller than the bandwidth of transmitted signal, then the channel creates frequency-selective fading on the received signal.
Fig. 3.1 Multipath fading due to multipath reflections. \( \tau \) denotes the different delays for the signals to travel from the mobile users to the basestation.

If the coherence time of the channel, which is a statistical measure of the time duration over which the channel impulse response is essentially invariant) is smaller than the symbol period of the transmitted signal, then the channel is known as a fast fading channel. On the other hand, if the channel impulse response changes at a rate much slower than the transmitted baseband signal, the channel is classified as a slow fading channel. In the IS-95 digital cellular telecommunication system, the transmitted signal is spread to a signal with very large bandwidth, which is usually larger than the channel coherence bandwidth, and the symbol rate is often higher than the channel impulse response changing rate. In this regard, the IS-95 channel is a slow
fading, frequency-selective channel. We will consider specifically Rayleigh fading in each path because in urban areas, Line-of-Sight (LOS) propagation path is not often available. This kind of environment consisting of non-LOS reflected paths is modelled by multipath Rayleigh fading with its probability density function (PDF) given by [30]

\[
p(r) = \begin{cases} 
\frac{r}{\sigma^2} \exp \left( -\frac{r^2}{2\sigma^2} \right) & (0 \leq r \leq \infty) \\
0 & (r < 0)
\end{cases}
\]

where \( r \) is the signal envelope amplitude, \( \sigma \) is the Root Mean Squared (RMS) value of the received signal and \( \sigma^2 \) is the average power of the received signal. Depending upon how this fading channel has been employed, it can be classified into two categories, namely the uncorrelated and correlated Rayleigh channel, which will be described next.

### 3.3.1 Uncorrelated Rayleigh Fading

Uncorrelated Rayleigh fading algorithm generates signal envelope amplitude and phase data in such a way that there is no temporal correlation between samples. The advantage is that it is very simple and is oftenly used in scenarios where temporal correlation is not needed such as 1st order estimation of the BER. The random Rayleigh envelope is given by [30]

\[
\beta = \sqrt{N_1(0, \sigma)^2 + N_2(0, \sigma)^2}
\]

where \( N_1(0, \sigma) \) and \( N_2(0, \sigma) \) are Gaussian distribution with mean \( \mu = 0 \) and standard deviation \( \sigma \). The phase is randomly generated in \([0, 2\pi)\) range.
3.3.2 Correlated Rayleigh Fading

While uncorrelated Rayleigh fading is useful for BER estimation and for calculating the average power of multipath component, it is not suitable to be a fading model for observing convergence performance of various adaptive algorithms. This is because these observations require temporal correlation in between the received signal amplitude and phases samples. Therefore, the software simulator described in [31] is used to generate correlated Rayleigh fading amplitudes and phases. Traditionally, conventional fading simulators for Jake’s model [23] uses digital filter to filter white Gaussian noise and to create the appropriate Doppler spectra. However, these simulators have the constraint that the filter must be implementable. As a result, approximation to the real world Doppler spectrum is often made. The method adopted in this thesis uses a Doppler spectrum generated by a direct summation of partial waves, which represents an exact replica of the actual physical situation. The time-dependent total wave field can be expressed as a sum of partial waves as was suggested in [42]

$$E_z(t) = \sum_{i=1}^{\infty} e_i \exp \left[ j \left( \varphi_i^0 + \frac{2\pi}{\lambda} vt\cos \alpha_i \right) \right]$$

(3.8)

where $e_i$ and $\varphi_i^0$ are the $i$-th partial wave amplitude and original phase and $\infty$ is the total number of scattered partial waves. The original phase is uniformly distributed between $[0, 2\pi)$, $\lambda$ is the signal wavelength, $v$ is the travelling speed of mobile and $\alpha_i$ is the $i$-th partial wave AOA.

To simulate a Rayleigh fading channel, $e_i$ needs to be solved and is given by
\[ \Omega = \mathbb{E}[x^2] \]  

(3.9)

where \( \Omega \) is the average power. The correlated Rayleigh amplitude \( \beta \) is then summed vector-wise and can be expressed as

\[
\beta = \sqrt{\sum_{i=1}^{\kappa} e_i \cos (\varphi_i^0 + \frac{2\pi v_i \cos \alpha_i}{\lambda}) + \sum_{i=1}^{\kappa} e_i \sin (\varphi_i^0 + \frac{2\pi v_i \cos \alpha_i}{\lambda})}^2. 
\]

(3.10)

whereas the correlated phase \( \phi \) is given by

\[
\Phi = \tan^{-1}\left[\frac{\sum_{i=1}^{\kappa} e_i \sin (\varphi_i^0 + \frac{2\pi v_i \cos \alpha_i}{\lambda})}{\sum_{i=1}^{\kappa} e_i \cos (\varphi_i^0 + \frac{2\pi v_i \cos \alpha_i}{\lambda})}\right]. 
\]

(3.11)

Fig. 3.2 shows typical Rayleigh fading amplitude fluctuations obtained by means of computer simulation for four different mobile user speeds over a time period of 0.52s. The time axis is expressed in terms of Walsh symbol for observing the signal amplitude fluctuations relative to each symbol period. Each Walsh symbol period\(^1\) corresponds to a duration of 208.3μs in IS-95 standard, which makes up to a total of 2500 Walsh symbols in the time duration of 0.52s. As it can be observed from Fig. 3.2 and as expected, the higher is the speed the mobile travelling, the more rapid is the fluctuation of the signal amplitude.

In our simulations later on, we need to generate this Rayleigh amplitude for channel modelling purposes. In order to reduce the simulation time as well as the usage of computer

\(^1\) As it will be reviewed in Chapter 4, in the IS-95 standard, each Walsh symbol consists of 256 chips.
resource, the Rayleigh fading amplitude is not updated every chip. Fig. 3.3 illustrates a magnified version of the Rayleigh amplitude fluctuations when the mobile is travelling at a speed of 50 km/hr. There is virtually no change in the amplitude in a duration of even 10 Walsh symbols at this high speed. In the IS-95 uplink simulation, each Walsh symbol period corresponds to 256 chip time period. To perform efficient simulation, the Rayleigh amplitude is only updated every 1/4 Walsh symbol, which corresponds to 64 chip time period, but not every chip.

![Fig. 3.2 The root mean squared (RMS) amplitude of Rayleigh fading when the mobile is travelling at 5km/hr, 15km/hr, 30km/hr and 50km/hr. For presentation purposes, the time unit is presented in terms of Walsh symbols to show the variation of amplitude in each Walsh symbol period. The entire time span in second is 0.52s](image-url)
3.3.2.1 Hashemi Model

When the multipath time delay spread is much smaller than the inverse bandwidth of the signal, paths are not resolvable and only one path is considered to be received at the antenna array. In this case, the single-path assumption is employed. However, in urban areas, time delay spread is around, or even could exceed, 4 μs [29][50]. This corresponds to a duration of 5 chip periods in IS-95 system, which are resolved into 5 multipaths at the receiver. While simplification to facilitate simulation is often made such that the average power at these 5 multipaths are equal to each other [19], in reality this is not true because the distribution of signal power in various paths depends on the channel communication environment.

Fig. 3.3 Magnified version of Rayleigh fading amplitude for mobile travelling at 50 km/hr
Hashemi conducted research of the urban radio propagation channel on four areas of urbanization, namely downtown San Francisco (large city), downtown Oakland (small to medium-sized city), downtown Berkeley (sub-urban area) and residential Berkeley (open rural area) [22]. The statistical properties of the arrival-time sequence \( \{t_k\} \) and amplitude sequence \( \{a_k\} \) for the \( k \)-th path are determined based on measurements for each of these urbanization categories. Signal phase \( \theta_k \) is assumed to be uniformly distributed on \([0, 2\pi)\). The data were then analyzed and the model of the channel was produced [22]. For our research, a program based on Hashemi model was used to generate signal amplitudes and time of arrivals [25]. In this program, the excess delay time axis for each path is divided into intervals of durations \( \Delta = 100 \text{ ns} \) called “bins”. Paths that are within the same bin are summed vector-wise to obtain the resultant amplitude. To conform to the IS-95 standard, vectors in every eight bins are further combined into one corresponding chip period duration of 4 \( \mu \text{s} \) long. The average power for the \( k \)-th excess delay bin (path) is then given by

\[
P_k = \left| a_{8k+1} e^{\theta_{8k+1}} + a_{8k+2} e^{\theta_{8k+2}} + \ldots + a_{8k+8} e^{\theta_{8k+8}} \right|^2 \tag{3.12}
\]

with \( \{a_i\} \) and \( \{\theta_i\} \) generated from the Hashemi model program and \( k = 0, 1, 2, \ldots \). Average multipath component power profile sets based on Hashemi model for multipath scenario are generated for each of the urbanization. The average power value in each bin is normalized so that the sum of average power in all the bins equals to unity.

3.3.2.2 Frequency-Selective Channel Model

Since the average power is not equally shared in each bin, in order to simulate a
frequency-selective fading channel, we need to take also into account the Hashemi multipath component power profile sets. Fig. 3.4 illustrates this frequency-selective channel model, where it is assumed that the transmitted signal of the form

\[ s(t) = \text{Re}\{b(t)\exp(j2\pi f_c t)\} \]  \hspace{1cm} (3.13)

will be received as

\[ r(t) = \text{Re}\{\rho(t)\exp(j2\pi f_c t)\} + n(t) \]  \hspace{1cm} (3.14)

with

\[ \rho(t) = \sum_{k=0}^{K-1} a_k \beta_k(t) b(t - \tau_k) \exp(j\Phi_k) \]  \hspace{1cm} (3.15)

In Eq. (3.13), \( b(t) \) is the transmitted information bit. In Eq. (3.15), \( K \) is the number of transmission paths, which is a random number and may vary from transmission to transmission, \( a_k = \sqrt{p_k} \) is the amplitude impulse response of the channel and \( p_k \) is the Hashemi average power bin for the \( k \)-th path, \( \tau_k \) is the \( k \)-th path excess delay due to the channel, \( n(t) \) is the additive white Gaussian noise (AWGN) component, \( \Phi_k = \eta_k + \vartheta_k \) is the temporally correlated phase for the \( k \)-th subpath and is between \([0, 2\pi)\), which is calculated by summing the phases \( \eta_k \) and \( \vartheta_k \). We note that \( \eta_k \) is generated by the Hashemi model and \( \vartheta_k \) is generated by the correlated Rayleigh fading model due to the introduced Doppler shift. It should be noted that in order for all paths to be resolvable, the following condition must be met
\[ |\tau_k - \tau_l| > 1/W, \quad \text{for all } k \neq l \]  

(3.16)

where \( W \) is the channel bandwidth.

Distinct paths in the physical medium that violate this resolvability condition are not counted separately, since they cannot be distinguished by measurements using bandpass signals with bandwidth \( W \). Instead, any two paths, say, path \( k_1 \) and \( k_2 \), for which \( |\tau_{k_1} - \tau_{k_2}| < 1/W \) are
considered as a single-path with a common delay $\tau_k \equiv \tau_{k_1} \equiv \tau_{k_2}$ and the amplitude and phase combination of the channel is given by [33]

$$a_k \beta_k(t) \exp(j \Phi_k) = a_{k_1} \beta_{k_1}(t) \exp(j \Phi_{k_1}) + a_{k_2} \beta_{k_2}(t) \exp(j \Phi_{k_2}).$$  \hspace{1cm} (3.17)

Hence, individual subpaths that are not resolvable are combined vector-wise to form a resultant Hashemi average power bin. Moreover, since the individual paths in these subpath clusters are usually close together spatially, they experience the same Rayleigh fading. Thus, Eq. (3.15) can now be simplified to

$$\rho(t) = \sum_{k=0}^{L_r-1} \sqrt{p_k} \beta_k(t) b(t - \tau_k) \exp(j \Phi_k).$$ \hspace{1cm} (3.18)

An excess delay of 4 $\mu$s is chosen so that $L_r$ is set to 5 multipaths in the IS-95 system. The time-delay blocks in Fig. 3.4 represent the resolution of the multipath delay profile. The incoming path signal entering the block is scaled by the Hashemi average power bin $p_k$ and multiplied by the corresponding temporally correlated Rayleigh amplitude $\beta_k(t)$. For the sake of simplicity, spatial correlation is omitted in this thesis so that each of the subpath clusters is considered to be statistically independent with each other and thus independent Rayleigh fading is assumed in each path. We also assume that the Hashemi sets $\{a_k\}$ and $\{t_k\}$ essentially remain constant throughout the duration of observation because the distances between the basestations and mobiles are relatively large compared to the mobile’s motion in that duration. In other words, we consider that the Hashemi average power bin $p_k$ remains constant.
3.4 Scattering Model

As previously mentioned, different signal paths arrive at the basestation at different angles because of the scattering. Since basestations are usually located at high places that are free of scatterers, and the scatterers are often crowded beside mobiles, a geometrically based circular model (GBCM) [34] (illustrated in Fig. 3.5) is used to generate AOA for different paths. Scatterers are assumed to be uniformly distributed inside a circle of radius $r$ around each mobile. The AOA from the mobile to the basestation and vice-versa can be calculated once the scatterer's coordinate has been randomly generated inside the scattering circle.

Fig. 3.5 Geometrically based circular scattering model with scattering radius $r$

3.5 Conclusions

In this chapter, we have presented the large-scale fading, small-scale fading and scattering models which will be used later in our simulations. Propagation loss and lognormal shadowing are the two major types of large-scale fading. A path loss component of 4 is usually assumed for propagation loss. The Hata Okumura model can be used for realistic path loss simulation. In this
model, the path losses of four urban areas, namely downtown San Francisco, downtown Berkeley, residential Berkeley and downtown Oakland are characterized. For lognormal shadowing, a standard deviation of 8 dB is assumed in this thesis. Rayleigh fading is classified as small-scale fading. For 1st order BER estimation, the uncorrelated Rayleigh fading model is usually used due to its simplicity. However, since we want to simulate the convergence performance of the adaptive nullsteering algorithms later in this thesis under Rayleigh fading environment, the correlated Rayleigh fading must be used to simulate the temporal correlation effect as well. The Hashemi model is used to generate the average power for each multipath component. Four different areas, namely downtown San Francisco, downtown Berkeley, residential Berkeley and downtown Oakland, are considered for this model. Since the IS-95 channel is classified as a slow fading, frequency-selective channel, the frequency-selective channel model is also considered in this chapter. Since the average power is not equally shared in each bin, in order to simulate this kind of fading channel, the average power, which is generated from the Hashemi model, has also been taken into account in this channel model. Finally, GBCM is used as a scattering model in this thesis.
Chapter 4  AN OVERVIEW OF THE IS-95 STANDARD

4.1 Introduction

In order to simulate the convergence performance of different adaptive algorithms for the IS-95 system as discussed in Chapter 2, we have to understand the underlying principle of the downlink and uplink transceiver in the IS-95 standard [24]. The purpose of this chapter is to familiarize with the IS-95 CDMA technology and the system architecture. The transceiver architecture presented in this chapter is used in conjunction with the adaptive algorithms presented in Chapter 2 to simulate the convergence performances of different adaptive algorithms in the IS-95 system, which will be presented in Chapter 5. The organization of this chapter is as follows. After this introduction, Section 4.2 presents an overview of the direct sequence (DS) spread spectrum techniques used in the IS-95 standard. Sections 4.3 and 4.4 introduce the IS-95 uplink and downlink traffic channel frame structure respectively, which are very essential in chip level simulation. Sections 4.5 and 4.6 describe the IS-95 receiver architecture for the uplink and downlink, respectively. Section 4.7 presents each individual block in these IS-95 downlink and uplink transceivers in further detail.

4.2 Direct Sequence (DS) Spread Spectrum Technique

This section is to provide an understanding of the underlying DS spread spectrum techniques employed by the IS-95 system. By using CDMA, multiple users can access the same channel bandwidth using the same carrier frequency and time slot. CDMA is proved to be a very vital tool in utilizing the usually limited bandwidth more efficiently and is more robust than traditional multiple access such as FDMA and TDMA [1]. In the IS-95 system, each user is given one out of a set of nearly orthogonal codes called Pseudo-Noise (PN) codes by which the data is
spread. Typically, the symbol rate \(1/T_s\) of a binary baseband data waveform is increased by multiplying it with this PN binary code waveform whose “chip” rate \(1/T_c\) is much faster than the symbol rate \(T_s = GT_c\). This concept is illustrated in Fig. 4.1. The effect of this operation will lead to the transmission of the signal in a radio frequency (RF) bandwidth substantially by \(G\) times (typically \(G \gg 1\)) greater than the information bandwidth. The bandwidth is spread because the power is conserved after spreading of the signal. As a result, the spectral density of the resultant waveform is lowered and becomes “noise-like”. This system is called Direct Sequence (DS) spread-spectrum system. By using this spread spectrum technique, even though users are operating on the same bandwidth, the spreading of the signal spectrum allows interference from other users to be suppressed. This property is found particularly useful in suppressing intentional jamming. In Fig. 4.1, by multiplying the same PN code with the received signal at the transmitter, the original data waveform and original bandwidth is restored, whereas the noise bandwidth remains the same. Upon filtering to the signal bandwidth, a gain in the SNR can be obtained and is given by

\[
(SNR)_{baseband} = \frac{A_0B}{N_0B} = \frac{A_0}{N_0} = G \cdot \frac{A_1}{N_0} = \frac{W}{B} \cdot (SNR)_{RF}
\]  

(4.1)

where \(G = W/B\) is known as the processing gain.

Apart from this gain, spread spectrum techniques provide data security because only the user with the original orthogonal code can demodulate the data correctly, other users will just receive noises when trying to decode with their own unique PN codes.

There are several channels used in IS-95 system, such as the pilot channel, paging channel
Chapter 4 AN OVERVIEW OF THE IS-95 STANDARD

and etc.

Fig. 4.1 Direct sequence (DS) spread spectrum System. (a) The original frequency spectrum (left) is spread when modulated by a PN sequence (right). (b) The time domain of the transmitted signal (left) when modulated by a PN sequence (right). (c) At the receiver, the jamming spectrum (left) is narrowed and lowered after filtering and despreading by the PN sequence. The received signal spectrum is recovered to original amplitude after despreading (right).

However, only the traffic channel carries the user information and will be discussed in this thesis. In the following sections, we will describe the basic structure of the uplink and downlink
traffic channels, which is essential in the development of an IS-95 chip-level adaptive nullsteering simulator for observing the convergence performance of the previously described adaptive algorithms. The uplink traffic channel is of much importance because of the inherent limited transmit power and is usually the limiting factor for improving the overall system capacity. Because of the difficulty in realizing the adaptive antenna physically at the mobile due to the size of antenna array and its complexity, the downlink will only be briefly studied in this thesis.

### 4.3 The IS-95 Uplink Traffic Channel

By the uplink traffic channel we mean the transmission from the mobile to the basestation and the block diagram of its frame structure is shown in Fig. 4.2. Acceptable voice quality can be achieved by transmitting data at a rate of 8600 bit per second (bps). With the Cyclic Redundancy Check (CRC) error-detecting code added, the total transfer rate becomes 9200 bps. For simplicity, in this thesis, we have assumed random binary bits generated at a rate of 9200 bps. 8-bit tail bits with all zeros are added to the data to give a total rate of 9600 bps. This group of transmitted bits is divided into 50 frames with each frame consisting of 192 bits. The frame is then passed through a rate $r = 1/3$ convolutional encoder with a constraint length $K = 9$. Each encoded frame now contains 576 bits. The coded symbols are then passed through a $(64,6)$ Walsh-Hadamard encoder for 64-ary orthogonal modulation. This Walsh-Hadamard encoder groups every 6 symbols and maps into one of the 64 possible Walsh sequences. Each frame now contains 96 Walsh sequences which is equivalent to a total of 6144 Walsh chips per frame (cpf).

A long-code PN generator generating a PN code with period $2^{42} - 1$ and running at a rate of 1.2288 Mcps is used to modulate the Walsh-Hadamard symbols. This long-code PN sequence spreads the symbols by a factor of 4. A short-code PN sequence is then used to modulate the
spread symbols at the same rate using Binary Phase Shift Keying (BPSK), resulting in a total of 24,576 chips per spread frame (csf). The modulated symbols are then low-pass filtered and transmitted with a carrier frequency of $f_c$.

![Diagram](image)

Fig. 4.2 Frame structure of the IS-95 uplink traffic channel

### 4.4 The IS-95 Downlink Traffic Channel

By downlink traffic channel we mean the transmission from the basestation to the mobile and the block diagram of its frame structure is shown in Fig. 4.3. Similar to the uplink traffic channel, the transfer rate of information data plus the CRC error-detecting code is 9,200 bps. Again, the transmitted data will be treated as random binary data for the sake of simplicity. Eight zero tail bits are concatenated with the data giving a total rate of 9,600 bps. This group of transmitted bits is divided into 50 frames and therefore each frame consists of 192 bits.
The frame is then passed through a rate $r = 1/2$ convolutional encoder with a constraint length $K = 9$. Each encoded frame contains 384 bits. A long-code PN generator generating a PN code with period $2^{42} - 1$ and running at a rate of 19.2 kbps is used to scramble the encoded frame for security purposes. However, for simplicity we omit this scrambler in this thesis. One of the 64 possible orthogonal Walsh periodic sequences is then modulo-2 added to the data stream at 1.2288 Mcps, thus increasing the rate by a factor of 64 chips/modulation symbol. This unique Walsh sequence is assigned to each forward traffic channel so that upon reception at their respective mobile stations, the traffic channels can be distinguished based upon the orthogonality of the assigned sequences. Finally, a short PN sequence at the same rate is used to modulate the orthogonally spread data stream by BPSK, making up a total of 24576 chips in each frame. It is then low-pass filtered and transmitted with a carrier frequency of $f_c$. 

Fig. 4.3 Frame structure of the IS-95 downlink traffic channel
4.5 The IS-95 Receiver for the Uplink

Fig. 4.4 shows the block diagram of an IS-95 receiver. Because of the absence of pilot signal in the uplink, non-coherent detection is used in the receiver. The received signal is downconverted and sampled to digital baseband. In each Rake finger, the signals in each arm are despread by multiplying them with the time-shifted user short PN and long PN code which are delayed by at least one chip in time from other fingers. The despread signals are then correlated with each of the 64 time-shifted Walsh functions. In the non-coherent maximal-ratio combiner, each of the 64 correlated Walsh value in the Rake finger is combined with the corresponding correlated Walsh value in other fingers, giving a total of 64 combined Walsh values. The estimated transmitted Walsh function is selected to be the one with the largest combined correlated Walsh value. This estimated transmitted Walsh function is then demapped to its corresponding 6 bits and are fed afterwards to a hard-decision Viterbi decoder to detect and decode the signal.

4.6 The IS-95 Receiver for the Downlink

Fig. 4.5 illustrates the IS-95 receiver for downlink. The signal received at the downlink receiver is first downconverted to digital baseband. In each Rake finger, a time-shifted short PN code which is delayed for at least one chip from other fingers is used to despread the baseband signal. The time-shifted Walsh function corresponding to the desired channel is then correlated with the despread signal. The correlated value from each finger is coherently maximal-ratio combined and passed to the decision device. Finally, the symbols are then decoded through a hard-decision Viterbi decoder. The main difference between the IS-95 downlink and uplink receiver is that the former demodulate the received signal coherently with the presence of pilot
signal. Since the transmitted power of mobile users is usually small, the pilot signal is absent in the uplink. As a result, non-coherent detection is used in the uplink receiver.

![Figure 4.4 IS-95 uplink receiver with L Rake fingers](image)

![Figure 4.5 IS-95 downlink receiver with L Rake fingers](image)
4.7 Individual Blocks in the IS-95 Transceiver

4.7.1 Introduction

As previously mentioned, BPSK is used as a modulation method in the IS-95 standard. A pseudo-noise (PN) random sequence is used to spread the transmitted signal and to despread the received signal. Walsh code is used to separate channels in the downlink and is used as a mean for non-coherent modulation in the uplink. Convolutional encoder is used for forward error control (FEC) purposes and finally the Rake receiver is used to combine incoming multipath signals so as to achieve a better SNR. The purpose of this section is to present these individual blocks in the IS-95 transceivers. The organization of this section is as follows. Section 4.7.2 presents the BPSK modulation method used in the IS-95 standard. Section 4.7.3 presents the algorithm to generate the PN sequence. Section 4.7.4 presents the Walsh code generator. Section 4.7.5 presents the convolutional encoder used in the forward and uplink. Finally, Section 4.7.6 presents the Rake receiver architecture.

4.7.2 Modulation

In the IS-95 standard [24], uplink traffic channel employs Quadrature Phase Shift Keying (QPSK) while downlink traffic channel employs Offset Quadrature Phase Shift Keying (OQPSK) modulation. In this thesis, we consider BPSK modulation for simplicity. To implement BPSK, binary data logical ‘0’ is represented by a negative sine wave, and logical ‘1’ is represented by a positive sine wave. The modulation process is usually accomplished through a level shifter, through which it transforms the logic ‘0’ to a digital voltage ‘-1’ signal and logic ‘1’ to a digital voltage ‘1’ signal. The carrier is then modulated onto the voltage forming the resultant signal. However, since only the baseband is considered in this thesis, the analog RF part is omitted.
4.7.3 PN Random Sequence

As mentioned, there are two kind of PN sequences used in IS-95 system. They are the short PN sequences and the long PN sequences. Short PN sequences are used to enhance the separation of the in-phase and quadrature-phase components by spreading both components with different code shifts for different cells in both downlink and uplink. However, since BPSK is used in this thesis, only one short PN sequence is used in the simulator for each cell. The long PN sequences are used differently in downlink and uplink and is unique for each user. In the downlink, they are used to scramble the data streams in order to provide enhanced security while in the uplink, they are used as a mean to spread the data thereby mitigating interferences.

To generate the short PN sequences, a simple linear feedback shift register implementation is used as shown in Fig. 4.6. The generator polynomials for the short PN sequence is:

\[ g(x) = 1 + x^3 + x^4 + x^5 + x^9 + x^{10} + x^{11} + x^{12} + x^{15} \]  

(4.2)

and the corresponding XOR mask for the linear feedback shift register is:

\[ (g_1, g_2, \ldots, g_{15}) = (001110001111001)_2. \]

(4.3)

There are a total of 15 registers which are required to generate a PN sequence with a period of \(2^{15} - 1\). This sequence is also called a maximal length sequence. The shift register is initially loaded with \((x_1, x_2, \ldots, x_{15}) = (100000000000000)_2\). The short PN sequences are pre-generated by this simulator and are stored in an array to increase processing speed.
Fig. 4.6 Short PN sequence linear feedback shift register block diagram

A linear feedback shift register shown in Fig. 4.7 is used to generate the long PN sequence. The 42-degree polynomial for long code is

\[ g(x) = 1 + x + x^2 + x^3 + x^5 + x^6 + x^7 + x^{10} + x^{16} + x^{17} + x^{18} + x^{19} + x^{21} + x^{22} + x^{25} + x^{26} + x^{27} + x^{31} + x^{33} + x^{35} + x^{42} \]

(4.4)

and the corresponding XOR mask is

\[ (g_1, g_2, \ldots, g_{42}) = (11101110010000011110110001010000001)_2 . \]

(4.5)

Since each of the users has a different long PN code, the initial contents of the registers \((x_1, x_2, \ldots, x_{42})\) are randomly modulo-2 generated. The state where all the registers are zeros is forbidden because it will produce an all-zero sequence which is not a valid maximal length sequence.
4.7.4 Walsh Code Generator

Walsh-Hadamard code set is a closed set of normal orthogonal functions. This orthogonality means that, if any two distinct functions are multiplied together and summed, the result is zero. Since they are also normal, this means if the two functions are one and the same, the integral of their product is unity. This property is very important for the IS-95 system, as it provides channel separation as well as a measure of coherence. The Walsh codes are used differently for the downlink and the uplink. In the forward traffic link, each channel is assigned an unique Walsh sequence so that upon reception at their respective mobile stations, the traffic channels can be distinguished based on its orthogonality of the assigned Walsh sequences. In the uplink, as the pilot signal is absent in the transmitted signal, non-coherent demodulation is used at the basestation. The use of Walsh sequence in this 64-ary orthogonal modulator provides a demodulation timing reference through demodulation of the coded 64 symbols.

The set of Walsh-Hadamard functions in the IS-95 system consists of 64 member
functions and is generated using Hadamard matrices by the following recursive process

\[ H_1 = [0] \]  \hspace{1cm} (4.6)

\[ H_{2N} = \begin{bmatrix} H_N & H_N \\ H_N & H_N \end{bmatrix}, \quad \text{where } N = 1, 2, 4, 8, 16, 32. \]  \hspace{1cm} (4.7)

However, the Walsh functions generated by the Hadamard matrix method are not indexed according to the number of sign changes. Considering the Walsh sequences of order \( 64 = 2^6 \) where \( O = 6 \), the Hadamard indices are rearranged according to the rule

\[ c_{k,0} = x_{k,1} \]
\[ c_{k,o - i} = x_{k,j} \oplus x_{k,j+1}, \quad j = 1, 2, \ldots, k - 1 \]  \hspace{1cm} (4.8)

where \( c_{k,i} \) is the \( i \)-th binary bit of the corresponding Walsh function index mapping from the \( k \)-th Hadamard function, \( x_{k,i} \) is the \( i \)-th binary bit of the \( k \)-th Hadamard function and \( \oplus \) denotes the modulo-2 addition.

In order to map the group of six bits to the corresponding 64 chip Walsh function in the encoder for the uplink, the Walsh sequence index \( i \) is chosen according to the following rule set forth in the IS-95 standard

\[ i = c_0 + 2c_1 + 4c_2 + 8c_3 + 16c_4 + 32c_5 \]  \hspace{1cm} (4.9)

where \( c_j \)'s are the coded symbol values for the index digits over \( \{0, 1\} \).
4.7.5 Convolutional Encoder

For both downlink and uplink, convolutional encoding schemes are used for FEC purposes, which improves the reliability of the communication system. In the uplink, the frame data stream is passed through a rate $r = 1/3$ convolutional encoder with a constraint length $K = 9$. The connection vectors are given by

$$
G_1 = (101101111)_2 = (557)_o \\
G_2 = (110110011)_2 = (663)_o \\
G_3 = (111001001)_2 = (711)_o
$$

(4.10)

and the encoder circuit for this code in the IS-95 standard is shown in Fig. 4.8.

In the downlink, a rate $r = 1/2$ convolutional encoder with a constraint length $K = 9$ is used instead. The connection vectors for the encoder are

$$
G_1 = (111101011)_2 = (753)_o \\
G_2 = (1011101001)_2 = (561)_o
$$

(4.11)

The encoder circuit for downlink is shown in Fig. 4.9.
Chapter 4  AN OVERVIEW OF THE IS-95 STANDARD

Fig. 4.8  Convolutional encoder for the uplink with rate $r = 1/3$ and constraint length $K = 9$
Fig. 4.9 Convolutional encoder for the downlink with rate $r = 1/2$ and constraint length $K = 9$
4.7.6 Rake Receiver

The Rake receiver takes advantage of the multipath signals by combining them so as to obtain a better SNR than normally a single-path can achieve. In a CDMA digital cellular system, the downlink uses a "three-finger" Rake receiver. A finger refers to the arm with a correlator as illustrated in Fig. 4.10. The uplink uses a "four-finger" Rake receiver. Because of the presence of the pilot signal in the downlink, signals from different paths are combined coherently. For the uplink, however, non-coherent maximal-ratio combining is used due to the lack of phase information. Fig. 4.10 depicts a general structure for a Rake receiver. The output from correlators are weighted by complex values $\alpha_0, \alpha_1, \ldots, \alpha_{L-1}$, which are set to be directly proportional to the correlator power output to give optimized combined SNR.

4.8 Conclusions

The direct sequence spread spectrum technique is presented in this chapter. Through this technique, interferences can be suppressed easily. As a result of that, CDMA cellular system can accommodate more users than the TDMA and FDMA systems. We have also considered the IS-95 uplink and downlink traffic channels. The frame structures of these channels are presented as well. Since the pilot signal is only present in the downlink but absent in the uplink, we have studied the coherent IS-95 downlink and the non-coherent uplink receivers. Individual blocks in the IS-95 transceiver, such as the modulator, PN random sequences, Walsh code generator, convolutional encoder and finally the Rake receiver have been also studied in detail. We will use these construction blocks in our convergence simulation in Chapter 5.
Fig. 4.10   General block diagram of IS-95 Rake receiver
Chapter 5  PERFORMANCE OF NULLSTEERING
ADAPTIVE ALGORITHMS FOR IS-95
CDMA SYSTEMS

5.1 Introduction

In this chapter we will study the detailed structure of both IS-95 CDMA transmitters and
receivers. In order to analyze and evaluate the performance of the different adaptive nullsteering
algorithms for the IS-95 downlink and uplink traffic channel, classic adaptive methods presented
in Chapter 2, i.e. the DMI, LMS and RLS algorithms, are modified to conform with the standard­
ized IS-95 receiver architecture. A chip-level IS-95 simulator is then implemented to evaluate the
convergence performances of these adaptive algorithms to the optimal adaptive nullsteering
weight vector solution. The organization of this chapter is as follows. After this introduction,
sections 5.2-5.3 present the IS-95 transmitter and receiver for the uplink traffic channel. In
sections 5.4-5.5 the IS-95 transmitter and receiver for the forward traffic channel are reviewed.
Section 5.6 then presents the adaptive nullsteering weight vector estimator in the basestation. To
adaptively estimate this weight vector, the adaptive algorithms are modified to be used in
conjunction with the IS-95 receiver and studied in Section 5.7. The convergence performance
results of these algorithms are then illustrated and discussed in Section 5.8. Finally, Section 5.9
proposes a power method based on these convergence performance results. This proposed power
method is used in Chapter 6 for efficient system capacity simulation.
5.2 IS-95 Uplink Traffic Channel Transmitter

![Block Diagram](image)

Fig. 5.1 shows a detailed block diagram of the IS-95 uplink transmitter. The transmitted signal for the k-th user \( s^{(k)}(t) \) can be mathematically expressed as

\[
 s^{(k)}(t) = \sqrt{2P} a_h^{(k)}(t) \cos(2\pi f_c t) \tag{5.1}
\]

where \( a_h^{(k)}(t) = C_L^{(k)}(t)C_S^{(k)}(t)H_h^{(k)}(t) , \) \( C_L^{(k)}(t) \) is the unique long PN signature of the k-th user, which is given by

\[
 C_L^{(k)}(t) = \sum_{i=-\infty}^{\infty} c_i^{(k)} p(t-iT_c) , \quad c_i^{(k)} \in \{-1, 1\}. \tag{5.2}
\]

\( C_S^{(k)}(t) \) is the short PN code for the k-th user, which is the same for users subscribing to
the same basestation,

\[
C_{s}^{(k)}(t) = \sum_{i=-\infty}^{\infty} c_{s}^{(k)} p(t-iT_{c}), \quad c_{s}^{(k)} \in \{-1, 1\}
\]

and \(H_{h}^{(k)}(t)\) is the \(h\)-th Walsh code for the \(k\)-th user,

\[
H_{h}^{(k)}(t) = \sum_{i=-\infty}^{\infty} H_{h}^{(k)} p_{w}(t-iT_{w}), \quad H_{h}^{(k)} \in \{-1, 1\}.
\]

In Eq. (5.1), \(P = \frac{E_{b}}{T}\) is the average transmitted power where \(E_{b}\) is the bit energy and \(T\) is the bit duration, \(p(t)\) and \(p_{w}(t)\) are rectangular pulses of unit amplitude and duration of \(T_{c}\) and \(T_{w}\) (Walsh chip duration) respectively where \(T_{w} = 4T_{c}\).

5.3 IS-95 Uplink Traffic Channel Receiver

Fig. 5.2 illustrates a general block diagram of the adaptive receiver architecture for the reverse traffic channel. For a more detailed presentation, all the component blocks in this adaptive receiver are illustrated separately in Figs. 5.3-5.6. Fig. 5.3 depicts the block diagram of the finger block. Fig. 5.4 shows the block diagram of the nullsteering processor. Fig. 5.5 illustrates the block diagram of the adaptive nullsteering weight vector estimator and Fig. 5.6 shows the detail diagram of the maximal ratio combining Rake receiver.
Fig. 5.2  IS-95 uplink traffic channel adaptive receiver
To the $\zeta$-th Nullsteering Processor

Fig. 5.3 Block diagram of the $\zeta$-th finger for the $m$-th antenna element
Fig. 5.4  Block diagram of the $\zeta$-th nullsteering processor
Chapter 5 PERFORMANCE OF NULLSTEERING ADAPTIVE ALGORITHMS FOR IS-95 CDMA SYSTEMS

Fig. 5.5 Block diagram of the $\zeta$-th adaptive nullsteering weight vector estimator

Fig. 5.6 Block diagram of the Rake receiver using maximal ratio combining
In the adaptive receiver, as shown in Fig. 5.2, \( r_m(t) = r_{\text{Im}}(t) + j r_{\text{Qm}}(t) \) is the complex input signal where \( r_{\text{Im}}(t) \) and \( r_{\text{Qm}}(t) \) are the in-phase and quadrature-phase component of the \( m \)-th antenna respectively, with \( m = 0, 1, 2, \ldots, M - 1 \). It is assumed that input signals \( r_m(t) \) at the front end has been downconverted to digital baseband at each of these antenna elements. The in-phase and quadrature-phase components are then passed to the finger block, which is shown in Fig. 5.3. In this finger block, the in-phase and quadrature-phase are time-aligned with the phases in other fingers producing \( r_{\zeta m}^{(k)}(t) \), which is given by

\[
 r_{\zeta m}^{(k)}(t) = r_m(t - \tau_{\zeta}). \quad (5.5)
\]

The time delay \( \tau_{\zeta} \) is usually estimated by correlating the basestation short PN code for the \( k \)-th user with the incoming signal. \( r_{\zeta m}^{(k)}(t) \) is then despreaded with the short PN code \( C_{S}^{(k)}(t) \) and the user-specific long PN code \( C_{L}^{(k)}(t) \) for the \( k \)-th user. Following that, the result is then correlated with the \( h \)-th Walsh function \( H_{h}^{(k)}(t) \), where \( h = 0, 1, \ldots, 63 \), to give the correlated value \( b_{h, m, \zeta}^{(k)} \) for the \( \zeta \)-th Rake finger at the \( m \)-th antenna element. \( b_{h, m, \zeta}^{(k)} \) can be expressed as

\[
b_{h, m, \zeta}^{(k)} = \int_{64T} [r_{\zeta m}^{(k)}(t)C_{S}^{(k)}(t)C_{L}^{(k)}(t)H_{h}^{(k)}(t)]dt. \quad (5.6)
\]

These 64 complex values are fed to the \( \zeta \)-th nullsteering processor, which is illustrated in Fig. 5.4, to be weighed optimally. In this nullsteering processor, the complex \( h \)-th Walsh correla-
tor outputs $b_{h,m,\zeta}^{(k)}$ from the same $\zeta$-th finger block at different antenna sensors are multiplied by a complex adaptive nullsteering weight vector $w_{m,\zeta}^{(k)}$ and combined across the different antenna elements. This complex weight vector $w_{m,\zeta}^{(k)}$ is estimated from the adaptive nullsteering weight estimator block, as shown in Fig. 5.5, and is distinct for each different finger and antenna element, and can be expressed as

$$w_{m,\zeta}^{(k)} = w_{l,m,\zeta}^{(k)} + jw_{Q,m,\zeta}^{(k)}$$

(5.7)

where $m < M$, $\zeta < L_r$ with $L_r$ being the total number of fingers used. The combined signals are then squared to eliminate the channel phase delay giving $g_{h,\zeta}^{(k)}$.

$$g_{h,\zeta}^{(k)} = \left| \sum_{m=0}^{M-1} b_{h,m,\zeta}^{(k)} w_{m,\zeta}^{(k)} \right|^2$$

(5.8)

Finally, as shown in Fig. 5.6, the resulting signals $g_{h,\zeta}^{(k)}$ are fed to the Rake receiver and combined through maximal ratio weighting across all the $L_r$ $h$-th Rake fingers to give an output $u_i$, which is given by

$$u_i = \sum_{l=0}^{L_r-1} \sqrt{2P_i^{(k)} \rho_i^{(k)}} g_{h,\zeta}^{(k)}$$

(5.9)

where $P_i^{(k)}$ and $\rho_i^{(k)}$ are the average transmitted power and Rayleigh amplitude of the $i$-th Rake
finger for the k-th user.

As shown in Fig. 5.2, there are a total of 64 Rake receivers with each of them corresponding to a different Walsh function. The 64 decision variables, \( u_i \), at the output of the Rake receivers, as shown in Fig. 5.6, are compared with one another. The Walsh function with the largest value is chosen to be the transmitted Walsh sequence \( \hat{H}_h(t) \). As illustrated in Fig. 5.2, it is then decoded by a hard-decision Viterbi decoder to get the final decoded data. To calculate the adaptive nullsteering weight vector, the estimated transmitted Walsh code \( \hat{H}_h(t) \) is fed back to the adaptive nullsteering weight vector estimator block. The data immediately after the removal of the short and long PN code \( x_{\zeta, m}^{(k)} \), as shown in Fig. 5.3, is essential for estimation of the adaptive nullsteering weight vector.

For a single-cell multipath model, the baseband in-phase and quadrature-phase received signal at the m-th antenna element, \( r_{I, m}(t) \) and \( r_{Q, m}(t) \) respectively, can be expressed as

\[
\begin{align*}
    r_{I, m}(t) &= \sum_{n=0}^{N-1} \sum_{l=0}^{L_r-1} \sqrt{P_l^{(n)}} \beta_l^{(n)} a_h^{(n)}(t-\tau_l^{(n)}) \\
    &\quad \cdot \cos(\phi_l^{(n)}) \exp(j\pi m \sin\alpha_l^{(n)}) + \sqrt{2n(t)} \cos(2\pi f_c t)
\end{align*}
\]  

(5.10)
In the above equation, $P_l^{(n)}$ is the received power for the $i$-th path of the $n$-th user and is estimated using the Hashemi model power profile, $\tau_l^{(n)}$ is the path delay of the $l$-th path for the $n$-th user and $\phi_l^{(n)} = \theta_l^{(n)} - 2\pi f_c \tau_l^{(n)}$ where $\theta_l^{(n)}$ is the correlated channel phase shift for the $l$-th path. Also, $n(t) = \sqrt{2}n_f(t)\cos(2\pi f_c t) + \sqrt{2}n_Q(t)\sin(2\pi f_c t)$ is the bandpass AWGN with power spectral density $N_0/2$, with $n_f(t)$ and $n_Q(t)$ being the zero-mean Gaussian noise of variance $N_0/4$. Independent Rayleigh fading of amplitude $\beta_l^{(n)}$ is assumed for each path $l$. $\tau_0^{(k)}$ is assumed to be zero for self-synchronization. Finally, $\alpha_l^{(n)}$ is the AOA of the $l$-th path of the $n$-th user. It should be noted that, for the single link multi-user case, $L_r = 1$ and $P_l^{(n)} = 1$ whereas, for stationary users, $\beta_l^{(n)} = 1$ and $\theta_l^{(n)} = 0$.

Assuming self synchronization for the $\zeta$-th path of the $k$-th desired user, the in-phase and quadrature-phase of the received signal at the $m$-th antenna element of the $\zeta$-th finger are
\[ r_{I, \zeta, m}(t) = s_{I, \zeta, m}(t) + I_{si(I, \zeta, m)}^{(k)}(t) + I_{mai(I, \zeta, m)}^{(k)}(t) + n_I(t) \]  
\[ r_{Q, \zeta, m}(t) = s_{Q, \zeta, m}(t) + I_{si(Q, \zeta, m)}^{(k)}(t) + I_{mai(Q, \zeta, m)}^{(k)}(t) + n_Q(t) \]

respectively, where

\[ s_{I, \zeta, m}(t) = \sqrt{P_{\zeta}^{(k)}} b_{\zeta}^{(k)}(t) \cos(\Phi_{\zeta}^{(k)}) \exp(j\pi m \sin \alpha_{\zeta}^{(k)}) \]  
\[ s_{Q, \zeta, m}(t) = \sqrt{P_{\zeta}^{(k)}} b_{\zeta}^{(k)}(t) \sin(\Phi_{\zeta}^{(k)}) \exp(j\pi m \sin \alpha_{\zeta}^{(k)}) \]

\[ I_{si(I, \zeta, m)}^{(k)}(t) = \sum_{l=0}^{L_r-1} \sqrt{P_{\zeta}^{(k)}} b_{l}^{(k)}(t - \tau_{l, \zeta}^{(k)}) \cos(\Phi_{l, \zeta}^{(k)}) \exp(j\pi m \sin \alpha_{l}^{(k)}) \]  
\[ I_{si(Q, \zeta, m)}^{(k)}(t) = \sum_{l=0}^{L_r-1} \sqrt{P_{\zeta}^{(k)}} b_{l}^{(k)}(t - \tau_{l, \zeta}^{(k)}) \sin(\Phi_{l, \zeta}^{(k)}) \exp(j\pi m \sin \alpha_{l}^{(k)}) \]

\[ I_{mai(I, \zeta, m)}^{(k)}(t) = \sum_{n=0}^{N-1} \sum_{l=0}^{L_r-1} \sqrt{P_{\zeta}^{(n)}} b_{l}^{(n)}(t - \tau_{l, \zeta}^{(n)}) \cos(\Phi_{l, \zeta}^{(n)}) \exp(j\pi m \sin \alpha_{l}^{(n)}) \]  
\[ I_{mai(Q, \zeta, m)}^{(k)}(t) = \sum_{n=0}^{N-1} \sum_{l=0}^{L_r-1} \sqrt{P_{\zeta}^{(n)}} b_{l}^{(n)}(t - \tau_{l, \zeta}^{(n)}) \sin(\Phi_{l, \zeta}^{(n)}) \exp(j\pi m \sin \alpha_{l}^{(n)}) \]

and \( \zeta \leq L_r - 1 \). In the above equations, \( s_{I, \zeta, m}(t) \) and \( s_{Q, \zeta, m}(t) \) are the in-phase and quadrature-phase of the desired signal, \( I_{si(I, \zeta, m)}^{(k)}(t) \) and \( I_{si(Q, \zeta, m)}^{(k)}(t) \) are the in-phase and quadrature-phase of the self interference due to multipath components other than the \( \zeta \)-th path, \( I_{mai(I, \zeta, m)}^{(k)}(t) \) and
$l_{mai}(Q, \zeta, m)^{(k)}(t)$ are the in-phase and quadrature-phase of the multiple access interference due to users other than the $k$-th user. $\tau_{l, \zeta}^{(n)}$ and $\phi_{l, \zeta}^{(n)}$ are the path delay and phase delay of the $l$-th path of the $n$-th user relative to the $\zeta$-th path of the $k$-th user, respectively.

After multiplying with the adaptive nullsteering weight vector and squaring the resulting signal, its power $q_{h, \zeta}$ is given by

$$q_{h, \zeta} = \left| \sum_{m=0}^{M-1} \int_{pT_w}^{(p+1)T_w} w_m^{(k)}(k) \left( s_{m, \zeta}^{(k)}(t) a_h^{(k)}(t) \right) dt \right|^2 \quad (5.20)$$

where $s_{m, \zeta}^{(k)}(t) = s_{l, \zeta}^{(k)}(t) + j s_{Q, \zeta}^{(k)}(t)$ and the interference power $u_{h, \zeta}$ is given by

$$u_{h, \zeta} = \left| \sum_{m=0}^{M-1} \int_{pT_w}^{(p+1)T_w} w_m^{(k)}(k) \left( r_{m, \zeta}^{(k)}(t) a_h^{(k)}(t) \right) dt \right|^2 - q_{h, \zeta} \quad (5.21)$$

where $r_{m, \zeta}^{(k)}(t) = r_{l, \zeta}^{(k)}(t) + j r_{Q, \zeta}^{(k)}(t)$.

After maximal ratio combining, the total signal power is calculated by summing all the projections on each Walsh orthogonal code as follows

$$S = \sum_{h=0}^{63} \sum_{\zeta=0}^{L_r-1} \left( \sum_{l=0}^{2P_{r}^{(k)} \beta_{l}^{(k)} q_{h, \zeta}} \right)^2 \quad (5.22)$$

Similarly, the total noise plus interference power after maximal ratio combining is given
Chapter 5 PERFORMANCE OF NULLSTEERING ADAPTIVE ALGORITHMS FOR IS-95 CDMA SYSTEMS

by

\[ I = \sum_{h=0}^{63} \left( \sum_{\xi=0}^{L_r-1} \sqrt{2P_{\xi}^{(k)} \beta_{\xi}^{(k)} u_h, \xi} \right)^2. \] (5.23)

Therefore, the total output SINR, \( \text{SINR}_{\text{Total}} \), of the \( p \)-th Walsh symbol for the multipath case is

\[ \text{SINR}_{\text{Total}} = \frac{S}{I}. \] (5.24)

5.4 IS-95 Downlink Traffic Channel Transmitter

Fig. 5.7 illustrates the detailed block diagram of an IS-95 downlink traffic channel. Assuming perfect power control, the transmitted signal from the \( k \)-th user can be expressed as

\[ s^{(k)}(t) = \sqrt{2P_{k}^{(k)}} a^{(k)}(t) \cos(2\pi f_c t). \] (5.25)

![Fig. 5.7 Simplified IS-95 downlink traffic channel transmitter. For simplicity, the scrambler is omitted in the simulation](image)

Each \( k \)-th user is assigned an unique \( k \)-th Walsh sequence, where \( 0 \leq k \leq 63 \). When the \( n-
th user is subscribing to the basestation, the antenna pattern at this basestation is optimized for this user. The interference power created by this pattern to the $k$-th user is thus scaled by a power modification factor $\gamma_n^{(k)}$ because this antenna pattern optimized for the $n$-th user. This power modification factor can be mathematically expressed as

$$\gamma_n^{(k)} = \left| \sum_{m=0}^{M-1} w_{m,R}^{(n)} \exp(-j\pi m \sin \alpha_n^{(k)}) \right|^2 \left/ \sum_{m=0}^{M-1} \left| w_{m,R}^{(n)} \right|^2 \right.$$  \hspace{1cm} (5.26)

where $R$ is the Rake finger of the uplink receiver with the strongest received power. $w_{m,R}^{(n)}$ is estimated from the adaptive nullsteering estimator of the uplink in Fig. 5.5, $\alpha_n^{(k)}$ is the AOA from the $k$-th user to the basestation subscribed by the $n$-th user. Furthermore, $a_k^{(k)}(t) = H_k^{(k)}(t)C_s^{(k)}(t)D^{(k)}(t)$ where $D^{(k)}(t)$ is the coded symbols for the $k$-th user and is given by

$$D^{(k)}(t) = \sum_{i=-\infty}^{\infty} D^{(k)} \cdot p(t - iT_d), \quad D^{(k)} \in \{-1, 1\}$$  \hspace{1cm} (5.27)

with $T_d = 64T_w$ being the coded bit duration.

5.5 IS-95 Downlink Traffic Channel Receiver

A single-cell single link model is implemented for the downlink traffic channel. Fig. 5.8 shows a detailed block diagram of the downlink employing a coherent receiver. It should be noted that, due to their relatively large size and complexity, in practice adaptive antennas are not implemented on mobile.
Chapter 5 PERFORMANCE OF NULLSTEERING ADAPTIVE ALGORITHMS FOR IS-95 CDMA SYSTEMS

The signal $r(t)$ arriving at the $k$-th user can be expressed as

$$r(t) = \sum_{n=0}^{N-1} \sqrt{2P_{\gamma_n^{(k)}}} \beta a_n^{(n)}(t) \cos(2\pi f_c t) + n(t).$$

(5.28)

Since the output SINR after the correlator at the receiver fluctuates greatly due to orthogonality between different Walsh codes, the SINR before the correlator is estimated instead to observe the convergence performance.

![Diagram](image)

**Fig. 5.8** IS-95 forward traffic channel coherent receiver for single-path environment

After removing the carrier and with low-pass filtering, the low-passed signal $S_{LP}(t)$ can be expressed as

$$S_{LP}(t) = \sqrt{P_{\gamma_k^{(k)}}} \beta a_k^{(k)}(t).$$

(5.29)

Since the interference is transmitted from the same basestation over the same channel as the desired signal, the Rayleigh fading amplitude $\beta$ remains the same. Thus the noise-plus-
interference $I_{LP}(t)$ is given by

$$I_{LP}(t) = \sum_{n=0 \atop n \neq k}^{N-1} \sqrt{P_{I_{n}}^{(k)}} \beta a_{n}^{(n)}(t) + n_{LP}(t)$$

(5.30)

where $n_{LP}(t)$ is the filtered AWGN $n(t)$. The signal $S_{w}(t)$ before the correlator becomes

$$S_{w}(t) = S_{LP}C_{k}(t)H_{k}(t)$$

$$= \sqrt{P_{I_{k}}^{(k)}} \beta a_{k}^{(k)}(t) C_{k}(t) H_{k}(t)$$

$$= \sqrt{P_{I_{k}}^{(k)}} \beta D_{k}(t).$$

(5.31)

The noise-plus-interference signal $I_{w}(t)$ before the correlator is then expressed as

$$I_{w}(t) = I_{LP}(t)C^{(k)}(t)H_{k}(t)$$

$$= \left[ \sum_{n=0 \atop n \neq k}^{N-1} \sqrt{P_{I_{n}}^{(k)}} \beta a_{n}^{(n)}(t) + n_{LP}(t) \right] C^{(k)}(t) H_{k}(t)$$

$$= \sum_{n=0 \atop n \neq k}^{N-1} \sqrt{P_{I_{n}}^{(k)}} \beta H_{n}^{(k)}(t) H_{k}^{(k)}(t) + n_{LP}(t) C^{(k)}(t) H_{k}^{(k)}(t).$$

(5.32)

Therefore, the average output SINR of the Walsh symbol before correlator for the downlink can be expressed as
\[ \text{SINR} = \frac{\sum |S_{w}(t)|^2}{T_{b} \sum |I_{w}(t)|^2} \] (5.33)

5.6 The Adaptive Nullsteering Estimator

As illustrated in Fig. 5.4, the adaptive nullsteering weight vector \( w_{m, \zeta} \) is updated at every Walsh symbol period in the adaptive processor. As it was pointed out in Section 2.4.5.4, because of their equivalency, either one of the MMSE (Eq. (2.30)), MSINR (Eq. (2.38)) or MVDR (Eq. (2.43)) algorithms can be used to calculate the steady-state solution of adaptive nullsteering weight vector in the estimator. For example, Eq. (2.43) can be used to calculate the adaptive nullsteering weight vector \( w_{m, \zeta} \). In this equation, \( R_{xx} \) is given by

\[ R_{xx} = E\{xx^*\} \] (5.34)

with \( x = \begin{bmatrix} x_{I,0,0} + jx_{Q,0,0} & x_{I,1,0,0} + jx_{Q,1,0,0} & \ldots & x_{I,M-1,0} + jx_{Q,M-1,0} \end{bmatrix}^T \) and \( r_{xd} \) is given by

\[ r_{xd} = E\{xd\} \] (5.35)

with \( d = \hat{H}_h(t) \). The array response vector \( \chi \) in Eq. (2.43) can be estimated using direction-finding algorithms such as ESPRIT, MUSIC or code filtering. In this thesis, it will be assumed that AOA of every users are known. However, because the mobile channel is changing frequently, the adaptive nullsteering weight vector is needed to be updated frequently in real time. There are
many adaptive algorithms which can serve this purpose. However, investigation of such adaptive algorithms are beyond the scope of this thesis. Instead, classic adaptive algorithms such as DMI, RLS and LMS will be used to estimate these weight vectors so as to demonstrate the SINR convergence performance. Nevertheless, it must be emphasized that in order to use them in conjunction with an IS-95 receiver, these algorithms are needed to be modified and this will be explained in the next section.

5.7 Modified Adaptive Algorithms

5.7.1 Modified DMI Algorithm

The DMI algorithm calculates the weight vector \( \mathbf{w} \) directly by estimating the matrices in Eqs. (2.30), (2.38) or (2.43). For Eqs. (2.30) and (2.43), \( \mathbf{R}_{xx} \) can be estimated using Eq. (2.48).

For Eq. (2.38), in order to estimate \( \mathbf{r}_{xd} \), the reference must be known. However, for the receiver architecture proposed in Fig. 5.2, the reference \( \mathbf{H}^{(k)}_{n}(t) \) cannot be generated until after a Walsh symbol period \( T_{w} \). Therefore, in order for the DMI algorithm to be used in an IS-95 receiver, the adaptive nullsteering weight vector needs to be updated every Walsh symbol period \( T_{w} \) and the correlation matrices need to be averaged for the whole period. Thus Eq. (2.48) should be modified as follows

\[
\mathbf{R}_{xx}\left(\frac{kT_{w}}{T_{c}}\right) = \alpha_{DMI} \mathbf{R}_{xx}\left(\frac{(k-1)T_{w}}{T_{c}}\right) + E\left[ \mathbf{x}\left(\frac{kT_{w}}{T_{c}}\right)\mathbf{x}^{*}\left(\frac{kT_{w}}{T_{c}}\right) \right]
\]

(5.36)

where \( k = 0, 1, 2, \cdots \) with
\[ E[x(i)x^*(i)] = \frac{T_c}{T_w} \sum_{\tau=0}^{T_w/T_c-1} x(i+\tau)x^*(i+\tau). \] (5.37)

If the MMSE nullsteering algorithm (Eq. (2.30)) is to be used instead, \( \hat{r}_{xd} \) can be estimated by modifying Eq. (2.50) to

\[ \hat{r}_{xd}\left(\frac{kT_w}{T_c}\right) = \alpha_{DMI} \hat{r}_{xd}\left(\frac{(k-1)T_w}{T_c}\right) + E\left[ x\left(\frac{kT_w}{T_c}\right)d\left(\frac{kT_w}{T_c}\right) \right] \] (5.38)

with

\[ E[x(i)d(i)] = \frac{T_c}{T_w} \sum_{\tau=0}^{T_w/T_c-1} x(i+\tau)d(i+\tau). \] (5.39)

If the MSINR nullsteering algorithm (Eq. (2.38)) is used, \( \hat{R}_{NI} \) can be estimated by modifying Eq. (2.49) to

\[ \hat{R}_{NI}\left(\frac{kT_w}{T_c}\right) = \alpha_{DMI} \hat{R}_{NI}\left(\frac{(k-1)T_w}{T_c}\right) + E\left[ NI\left(\frac{kT_w}{T_c}\right)NI^*\left(\frac{kT_w}{T_c}\right) \right] \] (5.40)

with

\[ E[NI(i)NI^*(i)] = \frac{T_c}{T_w} \sum_{\tau=0}^{T_w/T_c-1} NI(i+\tau)NI^*(i+\tau). \] (5.41)
5.7.2 Modified LMS Error Algorithm

Since a reference $H_n^{(k)}(t)$ can only be generated when the whole Walsh symbol is decoded, instead of updating the weight vector in each chip period $T_c$, the weight vector is updated every Walsh symbol and Eq. (2.53) is modified to

$$w \left( \frac{(k+1)T_w}{T_c} \right) = w \left( \frac{kT_w}{T_c} \right) - \mu \left\{ y_d \left( \frac{kT_w}{T_c} \right) - w^* \left( \frac{kT_w}{T_c} \right) x \left( \frac{kT_w}{T_c} \right) \right\}$$

(5.42)

where

$$E\{2\mu[y_d(i) - w(i)^*x(i)]x(i)\} = \frac{T_c}{T_w} \sum_{\tau = 0}^{T_w/T_c - 1} 2\mu[y_d(i + \tau) - w^*(i + \tau)x(i + \tau)]x(i + \tau).$$

(5.43)

5.7.3 Modified RLS Algorithm

Similarly to the modified LMS error algorithm, the RLS adaptive weight vector update equation is modified from Eq. (2.59) to

$$w \left( \frac{(k+1)T_w}{T_c} \right) = w \left( \frac{kT_w}{T_c} \right) - \mu \left\{ q \left( \frac{kT_w}{T_c} \right) - w^* \left( \frac{kT_w}{T_c} \right) x \left( \frac{kT_w}{T_c} \right) \right\}$$

(5.44)

where
5.8 Convergence Performance of the DMI, LMS and RLS Algorithms

To demonstrate the different convergence performances of these adaptive algorithms in an IS-95 system, the transmitter and receiver structure discussed earlier in this chapter have been implemented in software in conjunction with the modified adaptive algorithms described in the previous section.

A single-path single-cell IS-95 system with 40 users is constructed to demonstrate the convergence performance of adaptive algorithms. In this system, both downlinks and uplinks in static and Rayleigh fading environments are simulated. The AOAs of users are assumed to be known and are uniformly distributed in \((0, 2\pi]\). Fig. 5.9 illustrates the adaptive performances, obtained by means of computer simulation, in a static environment for the single-path, uplink system. In this figure, the output SINR is calculated using Eq. (5.24) with \(L_r = 1\) and \(\beta = 1\). The performance evaluation results show that by using the RLS algorithm, the output SINR converges to the steady-state value much faster as compared to the LMS algorithm. Following Eq. (5.24), since the SINR is expressed in terms of the adaptive nullsteering weight vector, this implies that the adaptive nullsteering weight vector estimated using RLS algorithm converges to its steady-state much faster as compared to the LMS algorithm. Although the DMI algorithm provides the fastest convergence rate to the steady-state when compared to other adaptive algorithms as shown in Fig. 5.9, in reality it has the highest hardware complexity among the rest because matrix

\[
g(i)[d(i) - w^*(i)x(i)] = \frac{T_w}{T_c - 1} \sum_{\tau = 0}^{T_c} q(i + \tau)[d(i + \tau) - w^*(i + \tau)x(i + \tau)] 
\]
inversion is involved in this algorithm. Furthermore, when comparing the steady-state SINR value obtained using the DMI, RLS and LMS methods to that using a non-adaptive antenna, the former methods provide a much higher SINR value than the latter, achieving a higher system capacity than a normal antenna system without the use of nullsteering smart antenna. In Fig. 5.9, it can also be seen that the SINR results for the power method and DMI algorithm are almost the same throughout the entire duration of simulation. This power method can be used to simulate the capacity of an IS-95 system efficiently and will be presented in detail in Section 5.9.

![Comparison of convergence performance between DMI, RLS, LMS, power method and that without adaptive antenna in static environment, single-path uplink traffic channel](image)
It should be also pointed out that the output SINR of using DMI, RLS and LMS all converges to the same steady-state SINR. Since the SINR is expressed in terms of the nullsteering weight vector as can be seen from Eq. (5.24), this implies the nullsteering weight vectors generated by these three methods all converge to the same steady-state solution which is known as the Wiener solution [13]. This Wiener steady-state weight vector solution will be used in the system capacity analysis employing nullsteering, which will be presented in Chapter 6. The power method is used to estimate this Wiener steady-state weight vector and will be presented in Section 5.9.

Figs. 5.10 and 5.11 illustrate the output SINR computer simulated performance results for a single-path and multipath uplink in a Rayleigh fading environment. The output SINR for the single-path in a Rayleigh fading environment is calculated using Eq. (5.24) with \( L_r = 1 \) whereas for the multipath uplink, the SINR is calculated using Eq. (5.24) with \( L_r = 3 \) where only the three strongest signals selected. The Rayleigh fading amplitude \( \beta \) for both cases is generated using Eq. (3.10). From both of the above SINR results, similar to the static channel case, DMI algorithm provides the best convergence performance. It should be noted that, it takes longer for the SINR using the LMS and RLS algorithms to converge to its steady-state value in this case compared to the static channel case. However, the SINR for DMI converges to the steady-state value in 1 Walsh symbol period as shown in Figs. 5.10 and 5.11, and is the same as in the static channel case. This is because the channel changing rate is not as fast as the Doppler rate of moving users. As we have mentioned in Chapter 3, for a user travelling at 50 km/h, there is no significant change in the amplitude of the signal in a duration of even 10 Walsh symbols. In other words, it means that there is almost no degradation in the performance of the DMI algorithm because its convergence rate is
faster than the Doppler rate of moving users.

Moreover, it can be seen from the performance results for the multipath channel with Rayleigh fading (see Fig. 5.11) that the SINR for each of the algorithms is lower than the corresponding methods for the single-path channel with Rayleigh fading (see Fig. 5.10). Firstly, this is because only the strongest three out of the five signals in the Rake fingers are combined in the multipath case. This results in some losses in the receiving power at the receiver. Secondly, the resulting SINR through non-coherent maximal combination of multipath signal components is always lower when comparing to the single-path case.

It should be also pointed out that, although the received signal power in each multipath component in a Rayleigh fading environment (Fig. 5.11) is lower than that of a single-path signal, all of the algorithms (DMI, LMS and RLS) for the multipath case are able to achieve the same convergence rate comparing to the single-path case (Fig. 5.10). For the multipath uplink with Rayleigh fading (see Fig. 5.11), assuming that the distances between scatterers and receiver are large as compared to the mobile’s motion, the adaptive nullsteering weight vectors estimated by all three adaptive algorithms converge again to the same steady-state weight vector solution as can be implied from their same optimal SINR values in the steady-state. From these results, it should be also noted that the DMI algorithm always enables the output SINR to converge within the first few Walsh symbol periods in both static and multipath fading environments. This means that, for a rapidly changing channel, such as the Rayleigh fading channel, there exists algorithms such as the DMI algorithm which enables fast convergence of the adaptive nullsteering weight vector to its steady-state value. Therefore, this justifies the use of the steady-state weight vector solution, which we have already presented in Chapter 2, for the system capacity analysis and
performance evaluation and will be discussed in detail in Chapter 5.

Fig. 5.10  Comparison of the convergence performances between DMI, RLS, LMS, power method and that without adaptive antenna in Rayleigh fading, single-path uplink traffic channel
Fig. 5.11 Comparison of the convergence performances between DMI, RLS, LMS, power method and that without adaptive antenna in Rayleigh fading environment in a multipath reverse traffic channel.
For the downlink case, since mobiles do not have antenna arrays, adaptive antennas are only implemented on the basestations. The basestation scales the transmitted signal by multiplying this signal with a weight vector in such a way that the interferences to other users are minimized. Since the same set of adaptive nullsteering weight vector is used in the downlink as in its uplink counterpart for each user-basestation pair, the convergence rate of the adaptive nullsteering weight vectors in the downlink can be expected to be the same as that of the uplink. Figs. 5.12 and 5.13 show the computer simulated convergence performance for different adaptive methods of single downlink under static and Rayleigh fading environment respectively. In Fig. 5.12, the SINR is obtained using Eq. (5.33) with $\beta = 1$, whereas in Fig. 5.13, the output SINR result is estimated using the same Eq. (5.33) but with $\beta$ obtained using Eq. (3.10). Similar to the SINR result for uplink case, the convergence rate of SINR to its steady-state value is the fastest with the use of DMI method, followed by RLS and then LMS. As we can see from these two figures, the convergence rates of SINR using RLS and LMS are faster for the static channel than the Rayleigh fading environment. A deep null appears in the output SINR for the LMS algorithm in the Rayleigh fading channel (see Fig. 5.13) is because of the deep null appears in the Rayleigh fading amplitude shortly before. This causes the LMS algorithm to erroneously create a false antenna pattern at the basestation which may suppress the desired user and enhance the signal power from interferers. As a result, the output SINR keeps dropping until the Rayleigh fading amplitude starts to rise again.

Again here and similar to the uplink case, all three adaptive methods converge to the steady-state weight vector solution, with the DMI method achieving the fastest convergence rate. Hence, we can draw a similar conclusion as in the uplink that there exists algorithms, such as the DMI algorithm, which enable the output SINR to converge within the first few chips even in a
Rayleigh fading environment. Since the output SINR can be expressed in terms of the nullsteering weight vector, this means that the weight vector converges within the first few chips as well. As a result of that, assuming the existence of algorithms such as the DMI method, the steady-state weight vector solution can be used directly in the system capacity analysis for downlink as well.
Fig. 5.12 Comparison of the convergence performances between DMI, RLS, LMS, power method and that without adaptive antenna in a static environment in a single-path forward traffic channel.
Fig. 5.13 Comparison of the convergence performances between DMI, RLS, LMS, power method and that without adaptive antenna in a Rayleigh fading, a single-path forward traffic channel.
5.9 The Power Method

5.9.1 Introduction

As mentioned in Section 5.8, the power method can be used to simulate the capacity of an IS-95 system efficiently. Owing to limited resource and high complexity, it is impractical to simulate the system capacity by implementing an IS-95 simulator for each user. Instead, the system capacity will be estimated according to the approach by Chan [25], which will be presented in detail in Chapter 6. In this approach, the received power and the AOA of users are assumed to be known. By using these information, the power method can be used to calculate the parameters required for the estimation of the adaptive nullsteering weight vector efficiently. This weight vector is then used to create the adaptive nullsteering antenna pattern in the system capacity analysis. The following section presented the power method for both single-path and multipath cases.

5.9.2 Derivation of Power Method for Single-Path and Multipath Environment

Firstly, for the single-path case, by rewriting Eq. (2.38), the adaptive nullsteering weight vector \( w_{MSINR}^{(k)} \) of the \( k \)-th user can be expressed as

\[
 w_{MSINR}^{(k)} = \Theta [R_{NI}^{(k)}]^{-1} \chi^{(k)} 
\]

(5.46)

where \( R_{NI}^{(k)} \) and \( \chi^{(k)} \) are the noise-plus-interference covariance matrix and the array response column vector of the \( k \)-th user respectively. The \( i \)-th component of \( \chi^{(k)} \) is rewritten from Eq. (2.11) and can be expressed as

\[
 \chi_i^{(k)} = i \pi \sin \theta_k 
\]

(5.47)
where \( \theta_k \) is the AOA of the \( k \)-th user. \( \mathbf{R}_{NI}^{(k)} \) for the \( k \)-th desired user can be calculated by using a non-adaptive power method, as derived in Appendix A, and can be mathematically expressed as

\[
\mathbf{R}_{NI}^{(k)} = \sum_{n = 0}^{N-1} \mathbf{P}^{(n)} \mathbf{X}^{(n)} \mathbf{X}^{(n)*} + \sigma^2 \mathbf{I}
\]  

(5.48)

where \( \sigma^2 \) is the variance of the AWGN, \( \mathbf{P}^{(n)} \) is the average power of the \( n \)-th user and \( \mathbf{X}^{(n)} \) is the array response column vector of the \( n \)-th user. Similarly, for the multipath case, the adaptive nullsteering weight vector \( \mathbf{w}_{MSINR}^{(k,t)} \) of the \( t \)-th path of the \( k \)-th user can be represented as

\[
\mathbf{w}_{MSINR}^{(k,t)} = \Theta[\mathbf{R}_{NI}^{(k,t)}]^{-1} \mathbf{X}^{(k,t)}
\]

(5.49)

where \( \mathbf{R}_{NI}^{(k,t)} \) and \( \mathbf{X}^{(k,t)} \) are the noise-plus-interference covariance matrix and the array response column vector of the \( t \)-th path of the \( k \)-th user respectively. The \( i \)-th component of \( \mathbf{X}^{(k,t)} \) is rewritten from Eq. (2.11) and can be expressed as

\[
\mathbf{X}^{(k,t)}_i = i\pi \sin \theta_{k,t}
\]

(5.50)

where \( \theta_{k,t} \) is the AOA of the \( t \)-th path of the \( k \)-th user. \( \mathbf{R}_{NI}^{(k,t)} \) of the \( t \)-th path of \( k \)-th user, as derived in Appendix B, is given by

\[
\mathbf{R}_{NI}^{(k,t)} = \sum_{n = 0}^{N-1} \sum_{l = 0}^{L_r-1} \mathbf{P}^{(n,l)} \mathbf{X}^{(n,l)} \mathbf{X}^{(n,l)*} + \sigma^2 \mathbf{I}
\]

(5.51)
where \( P^{(n,l)} \) is the average power of the \( l \)-th bin of the \( n \)-th user in the Hashemi power profile and \( \chi^{(n,l)} \) is the array response column vector of the \( l \)-th multipath component of the \( n \)-th user.

By substituting Eqs. (5.47) and (5.48) into Eq. (5.46), or Eqs. (5.50) and (5.51) into Eq. (5.49), the adaptive nullsteering weight vector \( w \) for the single-path or the multipath case can be quickly determined, respectively. With this weight vector, the output SINR values at the uplink IS-95 receiver are plotted in Figs. 5.9 - 5.11, and that for the downlink are plotted in Figs. 5.12 and 5.13 under different environments. In all the figures for the uplink, the steady-state output SINR values calculated using this power method is the same as that using other adaptive methods (DMI, RLS and LMS). This is due to the fact that the adaptive nullsteering weight vectors calculated by the power method and other adaptive algorithms are essentially using the same steady-state weight vector solution. Since the SINR value is calculated in terms of this weight vector solution, the SINR steady-state values is the same for all the algorithms. The minor discrepancy in the steady-state SINR values between these algorithms is because of the recursive update method used by DMI, RLS and LMS algorithms. For the downlink scenario (see Fig. 5.13), relatively large discrepancies exist between the output SINR values for the power method and the other adaptive algorithms in the Rayleigh fading channel. Moreover, the output SINR value for the power method does not fluctuate in the same way as that for the other adaptive algorithms, unlike that as seen in the uplink case. This is because of the fact that as only one basestation is considered in the single-path environment, the transmitted desired signal and interferences from this basestation are in the same channel. As a result of that, Eqs. (5.31) and (5.32) have the same Rayleigh fading amplitude parameter \( \beta \) and are cancelled out in the numerator and denominator of the output SINR expression in Eq. (5.33), provided that the AWGN power
is negligible comparing to the interference signal power. Hence the Rayleigh fading amplitude variation does not reflect in the output SINR for the power method in Fig. 5.13. Nevertheless, though the SINR values for the DMI, RLS and LMS algorithms are not exactly the same as that for the power method because of the absence of the parameter $\beta$ in the output SINR expression for the power method as stated above and also because of the recursive update method of DMI, RLS and LMS, it can be seen that they approximately converge to the mean value of the steady-state SINR of the power method. As a result of the above observations, the power method is used to estimate the noise-plus-interference covariance matrix in the adaptive nullsteering weight vector for both downlink and uplink in the system capacity analysis in Chapter 6.

5.10 Conclusions

In this chapter, the adaptive antenna transceiver architectures for the downlink and uplink in the IS-95 system are presented and simulated. Adaptive antenna is only simulated in the basestation because of the difficulty to implement the adaptive antenna array on the cellular phone practically. The three most important adaptive algorithms, namely the DMI, LMS and RLS algorithms, are considered in this thesis. The results in Figs. 5.9 - 5.13 show that firstly there is significant gain in the output SINR of smart antenna over the normal antenna. Secondly, it shows that the adaptive nullsteering weight vector converges to the steady-state value within the first few Walsh symbols in the uplink and the first few chips in the downlink with the DMI algorithm. Therefore, the steady-state adaptive weight vector is used directly in the system capacity simulation of the IS-95 cellular communication system in Chapter 6 to create the adaptive nullsteering antenna pattern. To estimate this adaptive nullsteering weight vector, the noise-plus-interference covariance matrix and the array response vector of the desired signal are required as input
parameters. Given the AOA of the incoming desired signal, its array response vector can be easily obtained. The noise-plus-interference covariance matrix can be calculated efficiently using the power method which is proposed earlier in this chapter given the received interference signal power and their array response vectors. The output SINR results for both downlink and uplink, which are calculated in terms of this weight vector, are plotted in Figs. 5.9 - 5.13. These results illustrate that this power method produces identical output SINR steady-state as other adaptive algorithms (DMI, LMS and RLS). Thus, the power method will be used in our system capacity simulation for the IS-95 system in Chapter 6.
Chapter 6  SYSTEM CAPACITY ESTIMATION: METHODOLOGY, RESULTS AND DISCUSSION

6.1 Introduction

This chapter presents the system capacity performance evaluation results for using adaptive nullsteering antenna in the IS-95 system. In order to update the adaptive nullsteering antenna pattern, the power method described in Chapter 5 is used to estimate the noise-plus-interference covariance matrix. The adaptive nullsteering weight vector can then be calculated from this matrix. The organization of this chapter is as follows. After this introduction, in Section 6.2, the environment and the system parameters for system capacity simulation are first presented. The simulation methodology used in this thesis to estimate the system capacity for both downlink and uplink of the IS-95 cellular communication system will be presented next. In order to estimate the system capacity, a parameter known as the “SINR threshold” is needed to be determined in advance. This parameter can be calculated based on a BER performance model which will be described in Section 6.3. Section 6.4 presents the IS-95 system capacity results when adaptive nullsteering antenna is used. The results are then compared with that using beamforming. Finally, in Section 6.5 the conclusions of this chapter are presented.

6.2 Simulation Parameters and Methodology

6.2.1 Simulation Parameters

We have considered a 3-tier cell structure which consists of a total of 19 hexagonal cells as shown in Fig. 6.1. Each hexagonal cell has a radius of \( r \) where \( r = 4 \) km for macro-cell environment simulation. Each cell has one basestation located at its center. For these basestations, the
cases of omnidirectional, 3-sectored and smart antenna are considered and simulated. However, for the mobile users, only omnidirectional antennas are simulated. Adaptive nullsteering antenna is used as the smart antenna technology in these basestations.

Fig. 6.1 A 3-tier cell structure consisting of 19 hexagonal cells. $r$ is the radius of each hexagonal cell.

The antenna array is assumed to be in ULA form, with each antenna component separated by a distance of $\lambda/2$. In the system simulations, the processing gain for the IS-95 CDMA cellular system is 128, voice activity of users is set to be 3/8 and the signal power allocated to the pilot is assumed to be 20% for the downlink. BPSK is used as the digital modulation scheme. For the uplink, a convolutional encoder with rate = 1/3 and constraint length = 9 is used and for the downlink, a convolutional encoder with rate = 1/2 and constraint length = 9 is used instead. For the multipath environment simulation, a 4-finger Rake receiver is used in the uplink, with one of them searching for the strongest path and a 3-finger Rake receiver is used in the downlink. For
large scale fading, the Hata-Okumura model is used to model the path loss for the 4 different urban areas, namely Downtown Oakland, Downtown San Francisco, Down Berkeley and Residential Berkeley [29]. Lognormal shadowing is assumed to be a lognormal random variable with a standard deviation of 8 dB. For small scale fading, independent uncorrelated Rayleigh fading is assumed in each path, with the average power of each multipath component modeled by the Hashemi model for the 4 different urban areas. The GBCM model is used to model the scattering effect in simulation, with the scattering radius set to 0.2 km. The BER is set to $10^{-3}$ for communication with adequate voice quality.

6.2.2 Simulation Methodology

Fig. 6.2 summarizes the overall simulation flow for the initial system parameters estimation. For efficient system capacity simulation, the individual parameters for each users (location, path losses and AOA of signals to each basestation) are generated at every beginning of the simulation. The location of each user is assumed to be uniformly distributed in the 19-cell system. As a result, their coordinates are generated randomly. Each user is then subscribed to the basestation that has the lowest path loss. The AOA of each user to each basestation is calculated based on their respective locations. For multipath simulation, the AOAs are generated using the GBCM scattering model described in Chapter 3. The multipath components of each user is then assigned the average power value set from one of the $10^4$ pre-calculated Hashemi power profile, with the component which have the absolute AOA assigned the largest power value [25]. The SINR threshold for the Hashemi power profile allocated to each mobile-basestation pair is then estimated for both reverse and downlink. For the single-path case, the SINR threshold is set to 5 dB for uplink and 7 dB for downlink [1].
Fig. 6.2 Simulation flow diagram for pre-estimation of the system parameters of basestations and users
For the multipath case, this SINR threshold is calculated for each set of the Hashemi power profiles based on the BER performance model [25], which will be described later in Section 6.3. Therefore, the user who is assigned the specific set of Hashemi power profile for their multipath components is also assigned the associated SINR threshold. After all the system parameters are generated, users are introduced randomly into the schedule queue for later system simulation.

6.2.3 Uplink Capacity Simulation

The simulation flow for the uplink system capacity estimation is shown in Fig. 6.3. The received power of each user at its subscribing basestation is set to be proportional to its corresponding SINR thresholds at the beginning. The transmitted power for each user is then calculated based upon the path loss between this user and its subscribing basestation, and the received power at its subscribing basestation. In order to calculate the adaptive nullsteering weight vector \( w \) for each mobile-basestation pair, the noise-plus-interference covariance matrix \( R_{NI} \) for each mobile-basestation pair is reset to a zero matrix initially. Random users are then added one-by-one from the schedule queue into the system for simulation. The antenna pattern on all the basestations for each user is initialized to the omnidirectional pattern by setting the nullsteering weight vector \( w = [1 \ 0 \ldots \ 0]^T \). \( R_{NI} \) is calculated based upon the interferences from other active users as follows.

For the single-path simulations, the array response vectors of different users at the desired user subscribing basestation are calculated using Eq. (2.14).
Chapter 6 SYSTEM CAPACITY ESTIMATION: METHODOLOGY, RESULTS AND DISCUSSION

A. Start

Set Received Power at Each Basestation Proportional to SINR

Calculate Transmitted Power of Each User

Reset $R_{NI}$ of Each Link

Introduce 1 More User into System

Reset Weight $w$ in Each Link to $[1 \ 0 \ ... \ 0]^T$ to Establish Omnidirectional Pattern

Determine $R_{NI}$ based on Interference Information

Estimate Adaptive Nullsteering Weight $w$ for Each Link

Recalculate Link Loss for Every Link

Recalculate Received Power for Each Link

Recalculate Interference to Each Link from Each User

Check If S/I ratio < SINR Threshold

Check If Broken Link Percentage > 0.01

YES

number of users = system capacity

END

Fig. 6.3 Simulation flow diagram for estimating the uplink system capacity
The power method, as described in Section 5.9, is used to calculate the $R_{NI}$ of the desired user subscribing basestation by substituting the array response vectors and the received power of the interferers into Eq. (5.48). The optimal vector $w$ for each mobile-basestation pair is then estimated using Eq. (5.46).

For the multipath simulations, unlike that for the single-path case, the antenna pattern of each multipath component arriving at the receiver has to be optimized. The array response vector for each multipath component of the interference signal is calculated using Eq. (2.14) similar to the single-path simulations, with other multipath components from the same user being treated as self interference. These array response vectors for the interferers and for the self interference are substituted into Eq. (5.51) to calculate the $R_{NI}$ for the specific desired user multipath component. The $w$ for each multipath component of the mobile-basestation pair is then estimated according to Eq. (5.49). This process is repeated for each multipath component of the desired user. The total link loss for every user-basestation pair is then updated taking into account the modified antenna pattern due to adjusted $w$. The received power of each user at its subscribing basestation and the interference from the other users to this basestation are re-calculated because of the updated antenna pattern. Each link between the desired user and its subscribing basestation is then examined whether the SIR is below the SINR threshold. The link is considered to be broken when the SIR drops below the SINR threshold. If the link is not broken, another random user will be added to the system from the schedule queue until the percentage of broken link reaches an outage of 1%. The total number of users in the system at that moment is known as the system capacity. Since this system capacity varies according to user locations, a sufficient number of runs $U$ where $U = 1000$ are performed to obtain a cumulative probability curve for the overall system capacity.
6.2.4 Downlink Capacity Simulation

Fig. 6.4 illustrates the simulation flow for the downlink system capacity estimation. The transmitted power from each basestation to each user is initialized to be proportional to the path loss experienced by each user. The total transmitted power from each basestation is then calculated by summing the individual required transmitted power for each subscriber. With this information, the interference power to each user can be calculated given the path loss between this basestation and the other users. The $R_{NI}$ for every mobile-basestation pair for the uplink is then reset to a zero matrix. Since the vector $w$ used in the downlink is the same as its corresponding uplink, in order to calculate the system capacity on the downlink, the $w$ for every mobile-basestation pair in the uplink is needed to be estimated first. As a result, the transmitted power of the users to their subscribed basestations is set to be proportional to their SINR threshold values as in the estimation process of the uplink capacity. Random users are introduced one-by-one into the system from the schedule queue. The percentage of total signal power transmitted to each user from basestation is then calculated. By using this information, the total signal power transmitted from the basestation can be obtained by summing all the power transmitted to its subscribers. By setting the uplink weight vector $w$ such that $w = \begin{bmatrix} 1 & 0 & \ldots & 0 \end{bmatrix}^T$, the antenna pattern is then initialized to the omnidirectional pattern for each user-basestation pair. The uplink and downlink losses for every mobile-basestation pair are then estimated taking into account this omnidirectional antenna pattern at the beginning. The $R_{NI}$ is calculated based on the total interference from the other active users same as the procedure carried out in the uplink capacity simulation for both single-path and multipath cases. The vector $w$ can then be estimated by substituting $R_{NI}$ into Eq. (2.38).
Estimate Transmitted Power from Each Basestation

Determine Interference to Each User

Reset $R_{NI}$ of Each Link

Estimate Transmitted Power of Users

Introduce 1 More User into System

Calculate Basestation Transmitted Power For Each User

Calculate Basestation Total Transmitted Power

Reset Weight $w$ in Each Link to $[1 \ 0 \ ... \ 0]^T$
to Establish Omnidirectional Pattern

Estimate Uplink and Downlink Losses

Calculate $R_{NI}$ for Each Link

(1)

Estimate weight $w$ for Each Link

Re-estimate Downlink Losses

Re-estimate Signal Power

Re-estimate Interference Power

Check If S/I ratio < SINR Threshold

NO

Check If Broken Link Percentage > 0.01

YES

END

Fig. 6.4 Simulation flow diagram for estimating the downlink system capacity
These weight vectors $w$ for the uplink are used in their corresponding downlink. Since the antenna patterns are changed due to these updated $w$, the downlink losses for every users are needed to be updated. The signal and the interference power arriving at each user on the downlink are re-calculated taking into account these updated downlink losses. The actual received signal power is obtained by deducting the pilot signal power from the original signal power. With these informations, the SIR at the basestation is then calculated and compared to the pre-estimated SINR threshold in Section 6.2.2. The downlink between each user and its subscribing basestation is then examined in the same manner as in Section 6.2.3. A cumulative probability curve for the system capacity results is then obtained.

6.3 BER Performance Model

This section presents briefly the BER performance model, which has originally been used by Chan [25]. This model is used to estimate the uplink and downlink SINR thresholds at a BER of $10^{-3}$ for different multipath components. This model is very useful in our simulations as it readily predicts the SINR threshold for a certain set of multipath components arriving at the basestations or the users.

As mentioned in Section 6.2.2, the multipath components of each user is assigned the average power value set from one of the $10^4$ pre-calculated Hashemi power profile. The BER performance model is then used to calculate the SINR threshold for each set of these multipath signal power profile. Given a specific modulation technique and coding method, a SNR threshold of 5 dB for forward channel and 7 dB for reverse channel is adopted to maintain an average BER of $10^{-3}$ which is adequate for voice quality. However, this assumption is too optimistic and is
dependent on the specific multipath environment [25]. In this BER performance model, each multipath component is independently Rayleigh faded because LOS path seldom exists in urban environment. A 4-finger Rake receiver is used in uplink and a 3-finger Rake receiver is used in downlink. With one of the fingers in uplink searching for the next strongest multipath component, only 3 Rake fingers are actually used in combining the incoming signals.

In the downlink traffic channel, because of the presence of the pilot signal, the received signals can be aligned with the same phase and thus combined coherently in the Rake receiver. However, in the uplink traffic channel, because of the absence of a pilot signal, non-coherent maximal ratio combining is used to combine received signals.

The Chernoff bound on $P_c$ for an unfaded Gaussian downlink channel with coherent demodulation and coherent maximal ratio combining is given by [35]

$$ P_c < \prod_{l=1}^{L} \exp \left( -\alpha_l^2 \cdot \frac{E_c}{N_0} \right) $$

(6.1)

where $\alpha_l^2$ is the relative path gain of a multipath component and $E_c/N_0$ is the SINR per chip. The average Chip Error Rate (CER) in a multipath Rayleigh fading environment is given by [35]

$$ P_c < \prod_{l=1}^{L} \left( \frac{1}{1 + \alpha_l^2 \cdot \frac{E_c}{N_0}} \right) $$

(6.2)
From Eqs. (6.1) and (6.2), the excess SINR for $L$ multipath Rayleigh fading channel over that required for an unfaded Gaussian channel can be computed to achieve any given value $\ln(1/P_c)$, where $P_c$ is the chip error probability [35]. Also, since from [35], for a BER of $10^{-3}$ and assuming a memoryless channel, the required $\ln(1/P_c)/r$ value is 3.2 dB [25] for the rate $r = 1/2$ convolutional encoder used in the IS-95 downlink, therefore, $\ln(1/P_c)$ is estimated to be 0.19 dB. With this value, the excess SINR can be calculated for different multipath profiles with different $\alpha_f^2$ using Eqs. (6.1) and (6.2). By adding the excess SINR for a $L$ multipath Rayleigh fading channel over that required for an unfaded Gaussian channel to the base SINR, which is 3.2 dB, the total SINR threshold for a BER of $10^{-3}$ can then be found.

For the uplink, the chip error probability $P_c$ for unfaded one-path Gaussian channel is founded by linear regression [25] and is bounded by

$$P_c < \exp[-10^{1.975\log(E_c/N_0) - 0.242}]. \quad (6.3)$$

For a BER of $10^{-3}$ and assuming a memoryless channel, the required SINR $\ln(1/P_c)/r$ value is 2.85 dB with a rate $r = 1/3$ and constraint length $K = 9$ convolutional encoder used in the IS-95 uplink [35]. From that, $\ln(1/P_c)$ is estimated to be -1.92 dB. In order to estimate the SINR threshold for a specific multipath power profile for the uplink, the excess SINR for $L$ multipaths Rayleigh fading channel over that required for an unfaded single-path Gaussian channel to achieve a given value $\ln(1/P_c)$ needs to be computed [25]. This is done by calculating the $P_c$
for a specific set of multipath components starting from a low SINR. A total of 90000 runs are repeated to calculate an average $P_c$. With this $P_c$, if the evaluation of the expression $\ln(1/P_c)$ is smaller than -1.92 dB, then the initial SINR is increased. This procedure is repeated until the evaluation of the expression $\ln(1/P_c)$ is equal to -1.92 dB. The excess SINR can then be found by subtracting the SINR in Eq. (6.3) from this SINR threshold. The final SINR threshold is then calculated by adding the excess SINR to the base SINR = 2.85 dB for a BER of $10^{-3}$.

6.4 Performance Evaluation Results and Discussions

6.4.1 Overview

Using the previously described methodology, we have evaluated the uplink and downlink capacity of the IS-95 system using 3-sectored antennas and adaptive nullsteering antennas. For single-path simulations, since the system capacity will be affected by the number of antenna elements used in the adaptive nullsteering antenna, we have also included the system capacity results for using adaptive nullsteering antenna consisting of 2, 4 and 8 omnidirectional antenna elements. As a point of reference, the system capacity using an omnidirectional antenna is also included in the figures to show the system capacity without using smart antenna. For multipath simulation, only the system capacity results for using adaptive nullsteering antenna with 4 omnidirectional antenna elements are included owing to limited computing resources. Following [22], four urban models, namely downtown San Francisco, downtown Berkeley, residential Berkeley and downtown Oakland, are considered in the multipath scenario. In general, for both the uplink and downlink cases, we have also considered the effect of the number of tier of cells in both the single-path and multipath cases. The system capacity performance evaluation results are considered to be steady-state and will be presented as a function of the cumulative probability of
the number of users in each cell. For a concise presentation, the average system capacity results will be calculated from the cumulative probability results and will be presented also in table forms. After this section, Sections 6.4.2 and 6.4.3 will present the single-path and multipath results for using adaptive nullsteering antenna respectively. Finally, in Section 6.4.4, the system capacity results for adaptive nullsteering antenna will be compared with the results for beamforming and from other researchers.

6.4.2 Single-Path Results

Fig. 6.5 shows the single-path system capacity results for using adaptive nullsteering smart antenna technology in the uplink with the average system capacity results presented in Table 6.1. The average system capacity $C$ is equal to

$$
C = \sum_{n=1}^{N} x_n \cdot p(x_n)
$$

(6.4)

where $N$ is the total number of distinct system capacity results, $x_n$ is the $n$-th system capacity value and $p(x_n)$ is the probability of this system capacity. $p(x_n)$ is calculated by

$$
p(x_n) = \frac{N_{x_n}}{N_T}
$$

(6.5)

where $N_{x_n}$ is the number of occurrence of $x_n$ and $N_T$ is the total number of simulation runs. In Fig. 6.5, the system capacity results using adaptive nullsteering antenna consisting of 2, 4, or 8 omnidirectional antenna elements are included, with the average system capacity results listed in Table 6.1
Chapter 6 SYSTEM CAPACITY ESTIMATION: METHODOLOGY, RESULTS AND DISCUSSION

![Graph showing system capacity results using adaptive nullsteering smart antenna with omnidirectional antenna elements.](image)

**Fig. 6.5** Uplink single-path system capacity results using adaptive nullsteering smart antenna with omnidirectional antenna elements

<table>
<thead>
<tr>
<th>No. of Omnidirectional Antenna Elements in the Array</th>
<th>Average System Capacity (users/cell)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>34</td>
</tr>
<tr>
<td>2</td>
<td>53</td>
</tr>
<tr>
<td>4</td>
<td>83</td>
</tr>
<tr>
<td>8</td>
<td>115</td>
</tr>
</tbody>
</table>

**Table 6.1** Average system capacity results for adaptive nullsteering antennas with 1, 2, 4 and 8 omnidirectional antenna elements in a 19-cell single-path uplink environments
As a point of reference, the system capacity using an omnidirectional antenna is also included in this figure. Our results indicate that by using an omnidirectional antenna, each cell can accommodate around an average of 34 users (see Table 6.1), which is consistent with the results obtained by Gilhousen et al. [1] and when using 2, 4 and 8 adaptive nullsteering omnidirectional antenna elements, the average system capacity is increased to an average of 53, 83 and 115 users/cell respectively. As expected, the proposed adaptive nullsteering antennas can increase the average system capacity by at least 19 users/cell. Moreover, it can be also seen from the same figure that by using more antenna elements, the system capacity can be further increased. In particular, by doubling the antenna elements in the array, each cell can accommodate an additional 30 - 32 users on average.

With the use of 3-sectored antenna, an approximate 3-fold increase in the system capacity can be achieved as expected and is illustrated in Fig. 6.6 with the average system capacity results listed in Table 6.2. Each cell can accommodate an average of 95 users/cell (see Table 6.2) by using the 3-sectored antenna, which is approximately 3 times than that using the single omnidirectional antenna as shown in Table 6.1. Similarly, when the adaptive nullsteering antenna array utilizes 3-sectored antenna as its antenna elements, a 3-fold increase in the overall system capacity has been also observed. In this case, each cell can accommodate approximately 214 users with the use of four 3-sectored antenna elements in the adaptive nullsteering antenna on average.

Fig. 6.7 depicts the system capacity results for both single-path uplink and downlink for adaptive nullsteering antenna and the corresponding average system capacity results are listed in Table 6.3. Two antenna arrays of 4 and 8 omnidirectional elements are considered for each of the cases.
Fig. 6.6 Uplink single-path system capacity results using ideal 3-sectored antenna and adaptive nullsteering smart antenna with four 3-sectored omnidirectional antenna elements

Table 6.2 Average system capacity results for omnidirectional antenna, ideal 3-sectored antenna and adaptive nullsteering antenna with four 3-sectored antenna elements in a 19-cell single-path uplink environments
Fig. 6.7  Single-path uplink and downlink system capacity results using 19-cell model employing adaptive nullsteering smart antenna

<table>
<thead>
<tr>
<th>No. of Omnidirectional Antenna Elements in the Array</th>
<th>Average Uplink System Capacity (users/cell)</th>
<th>Average Downlink System Capacity (users/cell)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>83</td>
<td>99</td>
</tr>
<tr>
<td>8</td>
<td>115</td>
<td>145</td>
</tr>
</tbody>
</table>

Table 6.3  Average system capacity results for adaptive nullsteering using 4 and 8 omnidirectional antenna elements in a 19-cell single-path, uplink and downlink environments
By using a 4 omnidirectional elements antenna array in the downlink, an average system capacity of 99 users/cell can be achieved (see Table 6.3). Comparing to its uplink, thus the downlink can achieve 16 more users/cell than the uplink on average. Similarly, by using the 8 omnidirectional elements array, each cell can accommodate 145 users in the uplink on average. Its downlink can accommodate an additional 30 users than its uplink. In both cases and as expected, it is clear that the uplink is always the limiting factor in the system capacity. As a result, in the following simulations, only uplink is considered.

The system capacity results using a 4 omnidirectional nullsteering antenna elements array are illustrated in Fig. 6.8 with the average results listed in Table 6.4. In this simulation, the effect of the numbers of cell on the system capacity is as shown in this figure. It can be seen that with a single-cell structure, the system can host 158 users (see Table 6.4). Whereas for 7 cell structure (2-tier cell structure), each cell can accommodate 94 users. For the 19 cell structure (3-tier cell structure), 83 users/cell can be attained.

Although with the use of a single-cell structure, the highest system capacity can be obtained, this result is too optimistic because interferences from other cells are neglected in this model. Clearly, the 19-cell structure model is the most realistic among the three models considered because in practice there will be always interference from users in the other cells and the effect of these interference cannot be ignored. Similarly, when four 3-sector nullsteering antenna sensors are used in the array, the single-cell model enables a total number of 389 users on average to be fit in a single cell as shown in Fig. 6.9 with the average results listed in Table 6.5. However, this is again too optimistic as interferences from users in other cells has not been considered.
Fig. 6.8  Comparison of single-path uplink system capacity employing four omnidirectional antenna elements using adaptive nullsteering in a single cell (1 cell), 2-tier cell (7 cell) and 3-tier cell (19 cell) model

<table>
<thead>
<tr>
<th>Simulation Model</th>
<th>Average System Capacity (users/cell)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-Cell</td>
<td>158</td>
</tr>
<tr>
<td>7-Cell</td>
<td>94</td>
</tr>
<tr>
<td>19-Cell</td>
<td>83</td>
</tr>
</tbody>
</table>

Table 6.4  Average system capacity results for adaptive nullsteering using 4 omnidirectional antenna elements in single-cell, 7-cell and 19-cell single-path uplink environments
Fig. 6.9 Comparison of single-path uplink system capacity employing four omnidirectional 3-sectored antenna elements using adaptive nullsteering in a single cell (1 cell), 2-tier cell (7 cell) and 3-tier cell (19 cell) model

Table 6.5 Average system capacity results for adaptive nullsteering using four omnidirectional 3-sectored antenna elements array in single-cell, 7-cell and 19-cell single-path uplink environments
For a multi-cell environment, as it can be seen for the case of the 19-cell model, each cell can actually accommodate an average of approximately 214 users. The result for the 1-cell simulation (see Fig. 6.9) has a larger span of system capacity values than for the 19-cell scenario because of the smaller cell area in the 1-cell simulation than in the 19-cell simulation. As a result, the probability of assigning users close to each other resulting in broken links in the 1-cell scenario is higher, which results in a lower system capacity limit in Fig. 6.9.

6.4.3 Multipath Results

In urban areas, signals are seldom transmitted in single-paths. Multiple reflections always occur and result in multipath propagation. Fig. 6.10 shows the system capacity result using a 4 omnidirectional nullsteering antenna elements array in multipath environment with the corresponding average system capacity listed in Table 6.6. In this scenario, the 19-cell model is considered for realistic simulation. In downtown San Francisco, being a highly density urban area, signals are transmitted as multipaths because of multiple reflections. Thus almost all the signal power is distributed in the first 5 Hashemi power delay bin. While for open rural areas, which is represented by the Residential Berkeley model, most signals are transmitted in a single-path. Therefore, in most of the cases signal power is distributed only in the first delay bin. Since non-coherent Rake combining is used in the uplink receiver, the multipath power profile with distributed multipath component signal power in all the bins will result in lower combined received power than that with most of the power concentrated in the first bin. As a result, the signal link in a high population density area such as downtown San Francisco always has higher SINR threshold, which results in a lower system capacity. In this case, the average system capacity is approximately 84 users/cell (see Table 6.6).
Fig. 6.10  The multipath uplink system capacity results using adaptive nullsteering with four omnidirectional antenna elements in a 19-cell model.

Table 6.6  Average system capacity results for adaptive nullsteering using 4 omnidirectional antenna elements array in 19-cell, multipath uplink environments
The system capacity using the Residential Berkeley model is 94 users/cell, while that of using the Downtown Berkeley and Downtown Oakland model is somewhere in between, which is approximately 91 and 92 users/cell on average, respectively.

The system capacity performance results for a 19-cell urban environment are compared to that for a 7-cell and single-cell model and are shown in Figs. 6.11 and 6.12 with the average system capacity results listed in Tables 6.7 and 6.8, respectively. The single-cell model again presents over optimistic results. In the residential Berkeley model, the system capacity has an average of 183 users/cell (see Table 6.8). Whereas for the 7-cell model, the system capacity for the Residential Berkeley model has an average of 106 users/cell (see Table 6.7), which is significantly lower than that of single-cell model because of the more interferences coming from the users in the second tier of cells.

6.4.4 Further Comparisons and Discussions

In this subsection, we will compare the previously presented adaptive nullsteering results with equivalent results obtained using beamforming antenna. The beamforming results are obtained from the program written by Chan [25]. Fig. 6.13 illustrates the system capacity performance results employing the beamforming antenna technology for single-path and the average system capacity results are listed in Table 6.9. These results are taken from [25] and serve as a reference for comparing the system capacity performance between adaptive nullsteering and beamforming. Similar to the adaptive nullsteering approach, the beamforming antenna is made up of 2, 4 or 8 omnidirectional antenna elements. The system capacity by using an omnidirectional antenna without beamforming is included in this figure for comparison as well.
Fig. 6.11  Multipath uplink system capacity results using adaptive nullsteering with four omnidirectional antenna elements in a 7-cell model

Table 6.7  Average system capacity results for adaptive nullsteering using 4 omnidirectional antenna elements array in 7-cell, multipath uplink environments
Fig. 6.12 Multipath uplink system capacity results using adaptive nullsteering with four omnidirectional antenna elements in a single-cell model.

Table 6.8 Average system capacity results for adaptive nullsteering antenna using 4 omnidirectional antenna elements array in single-cell, multipath uplink environments.
Chapter 6  SYSTEM CAPACITY ESTIMATION: METHODOLOGY, RESULTS AND DISCUSSION

Fig. 6.13  Uplink single-path system capacity results using beamforming smart antenna with 2, 4 and 8 omnidirectional antenna elements

Table 6.9  Average system capacity results for beamforming using 1, 2, 4 and 8 omnidirectional antenna elements in a 19-cell single-path uplink environments
As shown in Table 6.9, by using 2 omnidirectional antenna elements, the system capacity has an average of 53 users/cell. Whereas by using 4 and 8 omnidirectional antenna elements in the array, the system capacity has an average of 90 and 188 users/cell, respectively. Comparing this result to that by Liberti [5], the beamforming system capacity results are obviously lower in this thesis. Liberti shows that by using beamforming antenna which made up of 2 and 4 omnidirectional antenna elements, the system capacity has an average of 80 and 100 users/cell, respectively. The reason for this difference is that Liberti [5] used a 2 layer wedge cell geometry instead of a 3-tier hexagonal cell structure in this thesis. In our case the 3-tier hexagonal cell structure gives rise to larger interference and is more realistic. Hence it results in the relatively lower system capacity than that in Liberti’s result. For the case of beamforming, by doubling the number of antenna elements in the array, the system capacity increases non-linearly. For example, as it can be seen from Table 6.9, by using a 2 element beamforming antenna, an extra of 19 users can be added into each cell. With the use of a 4 element antenna, the extra number of users increases to 37 users/cell when compared to the result for a 2 element antenna.

Similarly, a 8 element antenna enables an extra of 98 users to be added to each cell when compared to the result for a 4 element antenna. Comparing these beamforming results to the adaptive nullsteering results summarized in Table 6.1, at first glance, we can conclude that beamforming has a better performance in terms of system capacity when compared to adaptive nullsteering at large number of antenna elements. For small number of antenna elements, such as 2 antenna elements, the system capacities achieved by using beamforming and nullsteering are almost the same. However, with the use of 4 or even 8 antenna elements, beamforming can achieve an extra of 7 or 73 users/cell on average, which seems to have better performance than adaptive nullsteering. The above results do not agree with the data in Tables 2.1 and 2.3, in which
adaptive nullsteering could achieve higher SIR, which in turn should result in higher system capacity. The reason behind this is that for the beamforming results presented in [25], no AWGN is assumed to be present and hence the beamforming weight formula does not take into account the AWGN. The beam formed by the beamformer can therefore track the user accurately. However, for adaptive nullsteering in this thesis, in order to estimate the adaptive weight vector, AWGN must be present in either Eq. (5.48) for single-path case, or Eq. (5.51) for the multipath case, otherwise the inverse of these matrices will become singular and the weight vector could not be estimated. Furthermore, the AWGN could not be set to a very small value either or else the weight vector could be inaccurately estimated. As a result, the AWGN must be set and this affects the accuracy of profiling the antenna pattern for MSINR reception. This effect is not too significant when there are just a few users in the system as can be seen in Fig. 2.9, where the nulls are just a little bit off the interferers’ AOAs. However, when there are many users in the system, problems may arise as the interferers’ AOAs are usually very close to each other. As a result, inaccurate adaptive weight estimation due to AWGN can result in profiling an non-optimal antenna pattern, thus achieve a lower system capacity compared to beamforming. Nevertheless, the presented adaptive nullsteering results are more realistic because in reality, AWGN is always present in the adaptive weight vector estimation.

Finally, Fig. 6.14 shows the system capacity results by using a 4 omnidirectional beamforming antenna elements in urban environments, with the average system capacity results presented in Table 6.10. The average system capacity results for Downtown San Francisco, Downtown Oakland, Downtown Berkeley and Residential Berkeley are 77, 100, 104 and 106 users/cell respectively (see Table 6.10).
Fig. 6.14  Multipath uplink system capacity results using beamforming with four omnidirectional antenna elements in a 19-cell model

<table>
<thead>
<tr>
<th>Urban Areas</th>
<th>Average System Capacity (users/cell)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Adaptive Nullsteering</td>
</tr>
<tr>
<td>Downtown San Francisco</td>
<td>84</td>
</tr>
<tr>
<td>Downtown Oakland</td>
<td>92</td>
</tr>
<tr>
<td>Downtown Berkeley</td>
<td>91</td>
</tr>
<tr>
<td>Residential Berkeley</td>
<td>94</td>
</tr>
</tbody>
</table>

Table 6.10 Average system capacity results for beamforming and adaptive nullsteering using four omnidirectional antenna elements array in 19-cell, multipath uplink environments. The system capacity results for adaptive nullsteering is taken from Table 6.6 and included here for convenient comparison with the results for beamforming
In this case, compared to the adaptive nullsteering cases shown in Fig. 6.10, adaptive nullsteering technology enables each cell to accommodate an additional 7 users than that using beamforming in the case of Downtown San Francisco. The performance of beamforming is poorer than adaptive nullsteering's because of the fact that downtown San Francisco is a high density urban area. As a result, the multipaths which arrive in the vicinity of the main beam of the antenna pattern will greatly deteriorate the system capacity. However, adaptive nullsteering will not be affected as much as beamforming by this because the maximum beam location is not always pointing at the AOA of the desired user. In lower density areas such as Downtown Oakland, Downtown Berkeley and Residential Berkeley, beamforming seems to achieve better system capacity than adaptive nullsteering. For example, in Downtown Oakland, Downtown Berkeley and Residential Berkeley, by using beamforming, each cell can accommodate an extra of 8, 13 and 13 users respectively. Again, similar to the single-path results, the system capacity results for adaptive nullsteering seems to be lower than the results for beamforming owing to the inaccurate estimation of the adaptive nullsteering weight vector which results in non-optimal received SINR.

The system capacity results for adaptive nullsteering in the multipath IS-95 system are also compared to the beamforming system capacity result by Naguib [19]. Since a 4 Rake fingers receiver is used to combine received signals in [19], the average system capacity result in [19] is expected to be higher than the results presented in this thesis. The results by Naguib are extrapolated for the case of a 4 omnidirectional antenna elements array and the average system capacity is around 105 users/cell for a BER of $10^{-3}$. As expected in this case, the system capacity result by Naguib is higher than the adaptive nullsteering results (see Table 6.10) in this thesis.

However, compared to the results for beamforming (see Table 6.10), the average system
capacity for residential Berkeley is 106 users/cell and is higher than the Naguib's result. This is due to the fact that the SINR threshold for a multipath power profile with power contained mostly in a multipath component, such as in residential Berkeley case, is lower than that with equal power distribution in all the multipath components as in Naguib's case. For Naguib's result [19], because of the non-coherent combination of multipath power distributed in several multipath components, it always gives a smaller combined power than the case with a large power value contained in a single bin as in the case of residential Berkeley in this thesis. This fact is further illustrated in the SINR threshold table in [25] by Chan. For downtown San Francisco, the system capacity result (77 users/cell) is much lower than that in [19]. This is because most of the power is distributed beyond the third bin for a heavily density environment. Hence the system capacity result is dependent on the environment. As a result, by allocating power in multipath components according to Hashemi profile, a much more realistic system capacity result can be obtained.

6.5 Conclusions

As a conclusion, adaptive nullsteering is very suitable for applications which have small number of users such as wireless LAN etc. because it enables high SIR at the receiver by allocating nulls approximately at the AOAs of interferers as shown in Chapter 2 even with the presence of AWGN. When the system contains a large number of users, however, a slight deterioration in the accuracy of the adaptive nullsteering weight vector due to the presence of AWGN may result in a lower system capacity. Although beamforming seems to have a more promising result, the beamformer is assumed to be able to track the desired user with absolute accuracy because AWGN is not considered in the weight vector estimation.
Chapter 7 CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

7.1 Conclusions

In this thesis, we have analysed and evaluated the capacity improvements of adaptive nullsteering antenna technology offers for IS-95 cellular CDMA system. The major contributions of the thesis are summarized as follows.

7.1.1 Investigation of Nullsteering Algorithms

We have thoroughly investigated the adaptive nullsteering algorithms, such as the MMSE, MSINR and MVDR algorithms and their applications using the basic adaptive antenna architecture. By using the MMSE algorithm, an adaptive nullsteering weight vector can be generated in such a way that the mean square error is minimized between the weighted output and the local reference. With MSINR, a weight vector can be formed where the weighted SINR is maximized. Through MVDR, the gain of the main beam in the antenna pattern is constrained so that no power is lost from the signal and at the same time with the noise variance is minimized. These three algorithms are equivalent to each other and without loss of generality the MSINR algorithm is used to generate the adaptive nullsteering weight vector in this thesis.

We have also compared the performances of beamforming, nullsteering and adaptive nullsteering in a system with small number of users. Beamforming is able to achieve a high SNR by steering the beam to the desired signal direction. However, it offers a very low SIR because it does not take into account of interference signals' statistics. In contrast, nullsteering enables high SIR at the receiver by directly allocating nulls to the AOA of interference signals in the antenna pattern. However, since the number of nulls is limited to the number of antenna elements used, it
is not suitable for system with large number of users. Adaptive nullsteering has both the advantage of beamforming and nullsteering by including the statistics of desired signals and interference signals in its weight vector estimation.

7.1.2 Convergence Performance of Adaptive Algorithms in IS-95 Cellular System

We have implemented the IS-95 uplink and downlink simulators. These simulators include the IS-95 transmitter as well as a Rake receiver with the adaptive antenna processor. Traditional adaptive algorithms such as DMI, LMS and RLS have been modified to conform with the IS-95 standard and are used in conjunction with adaptive nullsteering. Depending on the parameters available, various forms of steady-state Wiener equation can be used in this receiver to estimate the adaptive nullsteering weight vector. In this simulator, the reference signal is generated by decoding the incoming signal. This reference signal is then fed back to the adaptive antenna processor for nullsteering weight vector estimation.

We have simulated and compared the convergence performance between DMI, LMS, RLS and that without adaptive antenna using an IS-95 chip-level uplink simulator. Although these adaptive algorithms require different input parameters, they all enable the SINR to converge to the same steady-state value. Thus this shows the equivalency between various forms of Wiener steady-state equations. Through these algorithms, it has been shown that a much higher SINR can be attained at the receiver than that without an adaptive antenna. This implies the optimized antenna pattern is able to support a much higher system capacity than normal omnidirectional antenna. Among these three adaptive algorithms, DMI enables the fastest convergence rate of SINR to its steady-state value, while LMS is the slowest. However, the hardware complexity in implementing the DMI algorithm is the highest among the three. Nevertheless, through DMI, the
optimized nullsteering weight vector converges to its steady-state value in a few symbols even in rapidly changing Rayleigh channel. Hence the steady-state adaptive nullsteering weight equation can be used directly in our capacity simulation. This saves a lot of simulation time and resources as we do not have to perform chip-level simulation.

7.1.3 System Capacity Analysis and Comparisons

We have presented the system capacity results for uplink and downlink environment. The system capacity is limited by uplink. With adaptive antenna, significant improvement in system capacity can be achieved than that with only normal omnidirectional antenna. The system capacity results for adaptive nullsteering are more realistic than the presented beamforming results, because AWGN is included in the adaptive weight vector estimation. The presented beamforming results assume that AWGN is absent so that the beamformer can track the desired user with absolute accuracy.

We have also presented realistic system capacity results on urban environments. These results are realistic because unlike traditional simulation, which assumes equal distribution of power in all the multipath components, power distribution in the multipath components is generated according to the Hashemi model. As a result, the system capacity is dependent on the type of urban environment. In multipath environment, the system with adaptive nullsteering technology can accommodate more users than that with beamforming, especially in high density urban area such as Downtown San Francisco. In open rural area, the system can accommodate more users with the use of beamforming.

The 19-cell model is a more accurate system capacity simulation model because it includes the effect of interference signals from other cells. The single cell model gives over
optimistic result. However, it can still be used as a quicker alternative to compare the effect of beamforming, nullsteering and that without adaptive antenna on the system capacity.

7.2 Suggestions for Future Research

Robust Nullsteering Algorithms

In this thesis, we have only included several modified classical adaptive algorithm examples such as DMI, LMS and RLS. Each of them has their own advantages and disadvantages. There is always a trade-off between hardware complexity and convergence rate towards the estimation of the steady-state weight vector. As an example, although DMI enables the weight vector to converge quickly, its hardware implementation is relatively complicated. Therefore, it is very essential to develop a robust algorithm that enables fast steady-state weight vector convergence rate but at the same time requires minimal hardware so that it could be used in most digital signal processor in third generation cellular system.

Robust Nullsteering Algorithms in Indoor Applications

We have only investigated outdoor environment in this research. With increasing bandwidth demand and with severe Rayleigh fading in the indoor environment, the requirement for the adaptive nullsteering algorithm may be totally different. This is a quite promising project especially if the algorithm could be used in indoor wireless modem as nullsteering enables very high SIR at the receiver for system with small number of users. However, the requirement for nullsteering to be used in indoor environment will be very stringent due to severe fading. This implies that it is essential to develop an algorithm that enable very fast convergence rate to the steady-state weight vector.
System Capacity using Adaptive Nullsteering under Different User Traffic Conditions

Although we have considered realistic urban environments such as downtown San Francisco, downtown Berkeley, residential Berkeley and downtown Oakland, the distributions of streets and traffics have not been implemented. It will be worthwhile to incorporate a realistic geographic and traffic model to estimate an even more accurate system capacity. By using the available commercial Geographical Information Systems (GIS), it will even be possible to estimate the overall capacity in 3-dimensional environment.

An IS-95 Simulator using Adaptive Nullsteering Technology in System Capacity Simulation

This thesis is divided mainly into two parts. The first part is to develop an IS-95 simulator to investigate the convergence performances of various adaptive algorithms. The second part is to estimate the system capacity based on the BER performance model. Because it is very resource consuming to directly use the IS-95 simulator in system capacity simulation, power method is used instead to shorten the simulation time. However, even so, it takes a long time to generate each system capacity cumulative probability curve. Nevertheless, incorporating the IS-95 simulator directly into system capacity simulations has the advantage that, not only could we obtain accurate system capacity result, as an example, the power bit in the frame structure in the simulator can also be adjusted to simulate open loop and close loop power control as well. In this way, the effect of dynamic power adjustment on overall system capacity can be observed. Furthermore, non-ideal power control and finite power dynamic range effects could also be simulated realistically. As a result, it would be worthwhile to use the IS-95 channel simulator directly to estimate the system capacity for multi-cell environment.
Bibliography


[27] A. M. Earnshaw, "Investigating the Effects of Imperfect Digital Beamforming on Cell Capacity in a Cellular CDMA Communication System", IEEE International Conference on


Appendix A. DERIVATION OF EQ. (5.48)

The purpose of this appendix is to derive an expression of the power method for single path environment. In order to show that the noise-plus-interference covariance matrix of the k-th desired user can be mathematically represented as in Eq. (5.48), we begin by rewriting the baseband signal vector at the receiver as a combination of the in-phase and quadrature-phase component in Eqs. (5.10) and (5.11) with $L_r = 1$ and $l$ omitted for the single-path case. The baseband received vector is given by

$$
r(t) = \sum_{n=0}^{N-1} \sqrt{P^{(n)}(t)} \beta^{(n)}(t) a_h^{(n)}(t - \tau^{(n)}) \exp(j\varphi^{(n)}) \chi^{(n)}(t) + n(t) \tag{A.1}
$$

The explanations of parameters are repeated here for the sake of convenience. $N$ is the total number of users in the system, $j = \sqrt{-1}$, $P^{(n)}(t)$ and $\beta^{(n)}(t)$ are the instantaneous\(^1\) received power and Rayleigh amplitude of the n-th user at time $t$, $a_h^{(n)}(t) = C_L^{(n)}(t) C_S^{(n)}(t) H_h^{(n)}(t)$ is the product between the long PN code $C_L^{(n)}(t)$, the short PN code $C_S^{(n)}(t)$ and the $h$-th Walsh sequence $H_h^{(n)}(t)$ of the n-th user at time $t$, $\tau^{(n)}$ and $\varphi^{(n)}$ are the time delay and channel phase for the n-th user, $\chi^{(n)}(t) = [0, \exp(j\pi \sin\alpha^{(n)}(t)), \ldots, \exp(j\pi(M-1) \sin\alpha^{(n)}(t))]^T$ is the array response vector

\(^1\)In Eq. (A.1), the received power of the n-th user is represented as $P^{(n)}(t)$ instead of $P^{(n)}$ as in Eqs. (5.10) and (5.11) to highlight the fact that the received power is instantaneous. The same applies to the array response vector $\chi^{(n)}(t)$ and the Rayleigh amplitude $\beta^{(n)}(t)$.
of the $n$-th user with $M$ and $\alpha^{(n)}(t)$ being the number of antenna elements used and the AOA of the $n$-th user respectively. $n(t) \in G(0, \sigma^2 I)$ is the AWGN vector, where $\sigma^2$ is the variance of $n(t)$.

Without loss of generality, we shall assume that user $n = 0$ is the desired user. Because of self synchronization, the time delay $\tau^{(0)} = 0$. It is also assumed that the long and short PN codes are uncorrelated with the noise vector $n(t)$ and with each other. After despreading with the long and short PN code, the noise-plus-interference vector $NI^{(0)}(t)$, with user 0 as the desired user, becomes

$$
NI^{(0)}(t) = \sum_{n=1}^{N-1} \sqrt{P^{(n)}(t)p^{(n)}(t)\alpha^{(n)}(t-\tau^{(n)})\exp(j\varphi^{(n)})} \chi^{(n)}(0)C_L^{(0)}(t)C_S^{(0)}(t) + n(t)C_L^{(0)}(t)C_S^{(0)}(t), \tag{A.2}
$$

Since $E[NI^{(0)}(t)] = 0$, $E[C_L^{(0)}(t)] = 0$, $E[C_S^{(0)}(t)] = 0$ and $E[n(t)] = 0$, the noise-plus-interference covariance matrix $R_{NI}^{(0)}(t_1, t_2)$ is then

$$
R_{NI}^{(0)}(t_1, t_2) = E[NI^{(0)}(t_1)NI^{(0)}(t_2)^*]. \tag{A.3}
$$
Substituting Eq. (A.2) into Eq. (A.3), gives

\[
R_{NI}^{(0)}(t_1, t_2) = \mathbb{E}\left[ \sum_{n=1}^{N-1} \sum_{k=1}^{N-1} P^{(n)}(t_1) P^{(k)}(t_2) \beta^{(n)}(t_1) \beta^{(k)}(t_2) [a_h^{(n)}(t_1 - \tau^{(n)}) \cdot C_L^{(0)}(t_1) C_S^{(0)}(t_1) \cdot a_h^{(k)}(t_2 - \tau^{(k)}) C_L^{(0)}(t_2)] \exp(j \phi^{(n)}(t_1)) \exp(-j \phi^{(k)}(t_2)) \cdot \chi^{(n)}(t_1) \chi^{(k)}(t_2)^* \right] + \mathbb{E}\left\{ n(t_1) n(t_2) \cdot C_L^{(0)}(t_1) C_S^{(0)}(t_1) C_L^{(0)}(t_2) C_S^{(0)}(t_2) \right\}.
\]

(A.4)

Since the long code \( C_L(t) \) and the short code \( C_S(t) \) are uncorrelated, and the AWGN vector \( n(t) \) is also uncorrelated with these PN codes, \( R_{NI}^{(0)}(t_1, t_2) \) can thus be expressed as
\[ R_{N}^{(0)}(t_1, t_2) = \sum_{n=1}^{N-1} \sum_{k=1}^{N-1} \sqrt{P^{(n)}(t_1)P^{(k)}(t_2)} \cdot E\left\{ \beta^{(n)}(t_1)\beta^{(k)}(t_2) \right\} \]

\[ \cdot E\left\{ a_h^{(n)}(t_1 - \tau^{(n)}) \cdot a_h^{(k)}(t_2 - \tau^{(k)}) \right\} \cdot E\left\{ C_L^{(0)}(t_1)C_L^{(0)}(t_2) \right\} \]

\[ \cdot E\left\{ C_S^{(0)}(t_1)C_S^{(0)}(t_2) \right\} \cdot \exp(j\varphi^{(n)})\exp(-j\varphi^{(k)}) \]

\[ \cdot \chi^{(n)}(t_1)\chi^{(k)}(t_2)^* + E\{n(t_1)n(t_2)\} \]  

(A.5)

Also, since

\[ E\left\{ C_L(t_1 - \tau^{(n)})C_L(t_2 - \tau^{(n)}) \right\} = \Lambda\left(\frac{t_1 - t_2}{T_L}\right) \]  

(A.6)

\[ E\left\{ C_S(t_1 - \tau^{(n)})C_S(t_2 - \tau^{(n)}) \right\} = \Lambda\left(\frac{t_1 - t_2}{T_S}\right) \]  

(A.7)

\[ E\left\{ H_h(t_1 - \tau^{(n)})H_h(t_2 - \tau^{(n)}) \right\} = \Lambda\left(\frac{t_1 - t_2}{T_w}\right) \]  

(A.8)

where \( T_L, T_S \) and \( T_w \) are the periods of long PN code, short PN code and Walsh sequence respectively, and
\[ \Lambda \left( \frac{t_1 - t_2}{T_i} \right) = \begin{cases} 1 - \frac{|t_1 - t_2|}{T_i} & \text{for } |t_1 - t_2| < T_i \\ 0 & \text{otherwise.} \end{cases} \] (A.9)

Substituting Eqs. (A.6), (A.7) and (A.8) into Eq. (A.5), gives

\[
R_{NI}^{(0)}(t_1, t_2) = \sum_{n=1}^{N-1} \sqrt{p^{(n)}(t_1)p^{(n)}(t_2)} E \left[ \beta^{(n)}(t_1)\beta^{(n)}(t_2) \right] \Lambda \left( \frac{t_1 - t_2}{T_L} \right) \Lambda \left( \frac{t_1 - t_2}{T_S} \right) \\
\cdot \Lambda \left( \frac{t_1 - t_2}{T_w} \right) \Lambda \left( \frac{t_1 - t_2}{T_L} \right) \Lambda \left( \frac{t_1 - t_2}{T_S} \right) \chi^{(n)}(t_1)\chi^{(n)}(t_2)^* \\
+ \delta(t_1 - t_2)\sigma^2 I \Lambda \left( \frac{t_1 - t_2}{T_L} \right) \Lambda \left( \frac{t_1 - t_2}{T_S} \right). \]  

(A.10)

where \( \delta(t) \) is the well-known \( \delta \) function.

Therefore, the covariance matrix \( R_{NI}^{(0)}(t, t) \) is

\[
R_{NI}^{(0)}(t, t) = E[NI^{(0)}(t)NI^{(0)}(t)^*] \\
= 2\sigma^2_R \sum_{n=1}^{N-1} p^{(n)}(t)\chi^{(n)}(t)\chi^{(n)}(t)^* + \sigma^2 I. \]  

(A.11)

where \( \sigma^2_R \) is the variance of the Rayleigh distribution.

Similarly, for a static channel without Rayleigh fading, the received signal can be rewritten from (A.1) as
The covariance matrix $R_{NI}^{(0)}(t, t)$ for a static channel can be estimated through similar approach and is expressed as

$$
R_{NI}^{(0)}(t, t) = E[NI^{(0)}(t)NI^{(0)}(t)^*] \\
= \sum_{n=1}^{N-1} P^{(n)}(t)\chi^{(n)}(t)\chi^{(n)}(t)^* + \sigma^2 I. \quad (A.13)
$$

For both static and Rayleigh fading channel, the steady-state weight vector can be found easily using Eq. (5.46). Since we are only interested in the output SINR at the receiver and also since the scaling factor $2\sigma_R^2$ for the Rayleigh fading case does not affect the actual antenna pattern, assuming the effect of AWGN is negligible comparing to the interference signals, the scaling factor $2\sigma_R^2$ in Eq. (A.11) can be removed. Thus we obtain identical expressions for the covariance matrix for both the static and Rayleigh fading cases. In general, $R_{NI}$ for the $k$-th user can be expressed as

$$
R_{NI}^{(k)}(t, t) = \sum_{n=0 \atop n \neq k}^{N-1} P^{(n)}(t)\chi^{(n)}(t)\chi^{(n)}(t)^* + \sigma^2 I. \quad (A.14)
$$

For consistency and presentation purposes, the above equation is rewritten as
\[ R_{NI}^{(k)} = \sum_{n = 0}^{N-1} P^{(n)} \chi^{(n)} \chi^{(n)*} + \sigma^2 I. \] (A.15)
Appendix B. DERIVATION OF EQ. (5.51)

The purpose of this appendix is to derive a similar expression of the power method as in Appendix A for the multipath environment. In order to show that the noise-plus-interference covariance matrix $R_{NI}$ for the $m$-th path of the $k$-th desired user can be mathematically represented as in Eq. (5.51), the baseband signal vector of the receiver can be represented by combining the in-phase and quadrature-phase component in Eqs. (5.10) and (5.11) and is given by

$$r(t) = \sum_{n=0}^{N-1} \sum_{l=0}^{L_r-1} \sqrt{P^{(n)}(t)} \beta_l^{(n)}(t) a_h^{(n)}(t - \tau^{(n)}) \exp(j \varphi^{(n)}) \chi^{(n)}(t) + n(t) \quad (B.1)$$

where $L_r$ is the total number of Rake finger at the receiver and $\beta_l^{(n)}(t)$ is the Rayleigh fading amplitude for the $l$-th path of the $n$-th user. Other parameters have the same meaning as mentioned in Appendix A and are not repeated here.

Without loss of generality, we assume the path $l = 0$ of the user $n = 0$ is the desired path of the user which we want to optimize the antenna pattern for. With similar assumptions as in Appendix A, after despreading with the long and short PN code, the noise-plus-interference vector $NI^{(0,0)}(t)$ for the path 0 of the user 0 becomes
Appendix B. DERIVATION OF EQ. (5.51)

\[ N - 1 L_r - 1 \]

\[ N_1^{(0,0)}(t) = \sum_{n=1}^{N-1} \sum_{l=1}^{L_r-1} \sqrt{P_l^{(n)}(t) \beta_l^{(n)}(t) a_l^{(n)}(t - \tau_l^{(n)}) \exp(j\phi_l^{(n)})} \]

\[ \cdot \chi_l^{(n)}(t) C_L^{(0)}(t) C_S^{(0)}(t) + n(t) C_L^{(0)}(t) C_S^{(0)}(t). \] (B.2)

Since \( E\{N_1^{(0,0)}(t)\} = 0, E[C_L^{(0)}(t)] = 0, E[C_S^{(0)}(t)] = 0 \) and \( E[n(t)] = 0 \), the noise-plus-interference matrix \( R_{NI}^{(0,0)}(t_1, t_2) \) for the path 0 of the user 0 can be expressed as

\[ R_{NI}^{(0,0)}(t_1, t_2) = E[N_1^{(0)}(t_1) N_1^{(0)}(t_2)^*]. \] (B.3)

Substituting Eq. (B.2) into Eq. (B.3), gives
Appendix B. DERIVATION OF EQUATION (5.51)

\[ R_{NI}^{(0,0)}(t_1, t_2) = E \left[ \sum_{n_1=1}^{N-1} \sum_{l_1=1}^{L_r-1} \sum_{n_2=1}^{N-1} \sum_{l_2=1}^{L_r-1} \sqrt{P_{l_1}^{(n_1)}(t_1)P_{l_2}^{(n_2)}(t_2)} \beta_{l_1}^{(n_1)}(t_1) \beta_{l_2}^{(n_2)}(t_2) \right] \]

\[ \left[ a_h^{(n_1)}(t_1 - \tau_{l_1}^{(n_1)})C_L^{(0)}(t_1)C_S^{(0)}(t_1) \right] \cdot \left[ a_h^{(n_2)}(t_2 - \tau_{l_2}^{(n_2)}) \right] \]

\[ \cdot C_L^{(0)}(t_2)C_S^{(0)}(t_2) \exp \left( j\phi_{l_1}^{(n_1)} \right) \exp \left( -j\phi_{l_2}^{(n_2)} \right) \]

\[ \cdot \mathcal{X}_{l_1}^{(n_1)}(t_1)\mathcal{X}_{l_2}^{(n_2)}(t_2)^* \right] + E \left\{ n(t_1)n(t_2)C_L^{(0)}(t_1) \right\} \]

\[ \cdot C_S^{(0)}(t_1)C_L^{(0)}(t_2)C_S^{(0)}(t_2) \right\}. \quad \text{(B.4)} \]

Since the long code \( C_L(t) \) and short code \( C_S(t) \) are uncorrelated, and the AWGN vector \( n(t) \) is also uncorrelated with the PN codes, \( R_{NI}^{(0,0)}(t_1, t_2) \) can be expressed as
Appendix B. DERIVATION OF EQ. (5.51)

\[ R_{NI}^{(0,0)}(t_1, t_2) = \sum_{n_1=1}^{N-1} L_r^{-1} \sum_{l=1}^{n_1=1} \sum_{n_2=1}^{L_r-1} \sum_{l_2=1}^{n_2=1} \sqrt{P_{n_1}(t_1)P_{n_2}(t_2)} E[\beta_{l_1}^{(n_1)}(t_1)\beta_{l_2}^{(n_2)}(t_2)] \]

Substituting Eqs. (A.6), (A.7) and (A.8) into Eq. (B.5) and simplifying gives

\[ R_{NI}^{(0,0)}(t_1, t_2) = \sum_{n=1}^{N-1} \sum_{l=1}^{L_r-1} \sqrt{P_{l}^{(n)}(t_1)P_{l}^{(n)}(t_2)} E[\beta_{l}^{(n)}(t_1)\beta_{l}^{(n)}(t_2)] \]

\[ \cdot \Lambda\left(\frac{t_1-t_2}{T_L}\right) \Lambda\left(\frac{t_1-t_2}{T_S}\right) \Lambda\left(\frac{t_1-t_2}{T_W}\right) \]

\[ \cdot \Lambda\left(\frac{t_1-t_2}{T_L}\right) \Lambda\left(\frac{t_1-t_2}{T_S}\right) \chi_l^{(n)}(t_1)\chi_l^{(n)}(t_2) \]

\[ + \sigma^2 I \cdot \delta(t_1-t_2) \]

\[ \cdot \Lambda\left(\frac{t_1-t_2}{T_L}\right) \Lambda\left(\frac{t_1-t_2}{T_S}\right). \]
Therefore, the covariance matrix $R_{NI}^{(0,0)}(t,t)$ can be expressed as

$$
R_{NI}^{(0,0)}(t,t) = E[N(t)N(t)^*] \\
= 2\sigma_R^2 \sum_{n=1}^{N-1} \sum_{l=1}^{L-1} P_l^{(n)}(t)\chi_l^{(n)}(t)\chi_l^{(n)*} + \sigma^2 I. \tag{B.7}
$$

With the same argument as in Appendix A, the scaling factor $2\sigma_R^2$ can be dropped. As a result, in general, $R_{NI}$ for the $m$-th path of the $k$-th user can be expressed as

$$
R_{NI}^{(k,m)}(t,t) = \sum_{n=0}^{N-1} \sum_{l=0}^{L-1} P_l^{(n)}(t)\chi_l^{(n)}(t)\chi_l^{(n)*} + \sigma^2 I. \tag{B.8}
$$

For consistency and presentation purposes, the above equation is rewritten as

$$
R_{NI}^{(k,m)} = \sum_{n=0}^{N-1} \sum_{l=0}^{L-1} P_l^{(n)}\chi_l^{(n)}\chi_l^{(n)*} + \sigma^2 I. \tag{B.9}
$$