PREPARATARY WORKS

Chapter 4

PREPARATORY WORKS

4.1 INTRODUCTION

In this chapter various preliminary works undertaken and their performance analysis is discussed. The performance of conventional matched filter, decorrelating detector (decorrelator) and MMSE detector is validated first. In this case detectors are formed with the knowledge of the signature codes of all users, signal amplitude etc. Next a data-aided adaptive MMSE detector is formed and the performance is validated. Blind versions of detectors are then developed and tested. Minimum variance and subspace methods are then simulated. The subspace-tracking algorithm is also attempted. Channel estimation using subspace method is also tried.

4.2 CONVENTIONAL MATCHED FILTER

Single-user matched filter or conventional matched filter (CMF) is the simplest detector for demodulating CDMA signals. CMF is an optimum receiver in single-user channel (only one user using the channel). But in a multiuser channel (More than one user using the channel), CMF ceases to be an optimum receiver when the signature codes of the users are non-orthogonal. This detector neglects the presence of other users in the channel and assumes that aggregate noise plus interference is white and gaussian. Fig. 4.1 is a plot of the bit error rate for the first user as a function of SNR, for two amplitudes of the interferer. We can observe the degradation of the BER, when the interfering user’s amplitude changes from zero to
The performance degradation due to the presence of other users is termed as near-far problem in multiuser communications.

Bit error performance of the decorrelator and CMF is compared in Fig. 4.2. It can be seen that bit error performance of the decorrelator is independent of the interferer’s amplitude, while the performance of the CMF is dependent on the amplitude of the interferer. In this respect decorrelator is near-far resistant. It can also be verified that at low SNRs there is no special advantage with the decorrelator and at very low SNRs the performance of the decorrelator is inferior to the CMF.
Moreover the decorrelator is not that attractive as the amplitude of the interferer comes down.

Fig. 4.2 BER comparison of the Decorrelator and CMF

4.4 MMSE DETECTOR

The conventional matched filter is optimized to combat the background white noise exclusively, whereas the decorrelating detector eliminates the multiuser interference disregarding background noise. In contrast, the MMSE linear detector can be seen as a compromise solution that takes into account the relative importance of each interfering user and background noise. In fact both conventional receiver and decorrelating receiver are limiting cases of MMSE linear detector. As MMSE detector converges to the decorrelating detector when $\sigma \to 0$, its asymptotic multiuser
efficiency and near-far resistance are identical to that of the decorrelator. The chief advantage of MMSE detector is the ease with which it can be implemented adaptively.

The Fig. 4.3 compares the BERs of the conventional matched filter, decorrelator and MMSE detector for two users with cross-correlation equal to 0.8. The SNR of the desired user is equal to 10 dB. The probability of error is shown against the near-far ratio $A_2/A_1$. Note that for sufficiently low interferer power, the probability of error of MMSE detector is better than that of the decorrelator. For relatively high-power interferers, the MMSE detector is quite similar to the decorrelator and much better than the conventional matched filter.

Fig. 4.3 BER comparison of CMF, Decorrelator and MMSE receiver at SNR=10 dB
4.5 ADAPTIVE IMPLEMENTATION

From chapter 3, it was clear that the formation of a decorrelator requires the cross correlation matrix of the signature codes and its inversion. MMSE detector additionally requires signal and noise amplitudes for its implementation. The complexity arising out of matrix inversion can be totally avoided by using adaptive implementations. It is particularly important to eliminate the need to compute the linear detector impulse response in asynchronous channels where cross correlations are time varying and in channels with time varying characteristics. It is desirable to have detector that do not require the knowledge of signal and noise amplitudes and signature codes of the users. The adaptive implementation of the receiver meets these requirements.

The training sequence-based (data-aided) adaptive MMSE detector learns the desired filter impulse response, from the received data provided the received sequence is previously known to the receiver. The bit error performance of a training based MMSE detector [9, Sec. 6.4] is contrasted with that of the non-adaptive MMSE detector in a three-user system in Fig. 4.4. Here we have used the technique of stochastic gradient descent, using LMS algorithm. It can be seen that performance-wise there is no much difference between adaptive and non-adaptive methods.
4.6 BLIND METHODS

4.6.1 Direct matrix inversion

A blind detector can be implemented either in batch mode or in adaptive mode. If the autocorrelation matrix of the received signal, $R = E\{rr^H\}$, is given then the MMSE detector $m_1$ is determined as

$$m_1 = |A_1|^2 R^{-1} s_1$$

(4.1)

Note that, $R$ can be estimated from the received signals by the corresponding sample autocorrelation. The above equation, leads straight forwardly, to the blind implementation of the linear MMSE detector, resulting detector is called, direct
matrix inversion (DMI) blind detector [24]. Here we do not assume knowledge of the amplitude of the desired user, so differential detection is employed as shown,

\[
\hat{R} = \frac{1}{M} \sum_{n=1}^{M} r(n)r(n)'^H, \quad \text{where} \ M \ \text{is the symbol length}
\]

\[
\hat{m}_1 = \hat{R}^{-1} s_1
\]

\[
z_i[n] = \hat{m}_1'^H r[n]
\]

\[
\hat{\beta}_1[n] = \text{sign}\{\text{Re}(z_i[n]z_i[n-1]^*)\}
\]

\[\text{(4.2)}\]

Fig. 4.5 Blind MMSE detector using DMI

The above method is a batch process method, which computes the detector only once, based on a block of received signals \(\{r[n]\}_{n=1}^{M}\). The performance comparison is shown in Fig. 4.5.
4.6.2 Blind adaptive implementations

MOE-LMS

In this section we discuss the performance of a blind, adaptive detector that converges to the MMSE detector without requiring training sequences. The knowledge required by the detector presented in this section is identical to the knowledge required by the conventional matched filter (CMF) receiver, namely the signature code and timing of the desired user. The approach we adopt here is same as the training based system, namely, stochastic gradient descent of a convex penalty function. In this case the penalty function is the output variance instead of mean squared error. This method is termed as minimum output energy (MOE) method.

In Fig. 4.6, we have demonstrated the close relationship between MOE and MMSE methods. It has been established that there is no theoretical difference between MOE and MMSE methods [9,13].

![Fig. 4.6 Performance comparison of adaptive MOE-LMS and ideal MMSE](image-url)
MOE-RLS

Here we are assessing convergence dynamics of an adaptive, blind MMSE detector formed, using MOE criterion and RLS algorithm. PN codes of length 31, are used as the signature codes. There are three interferers at 5, 10 and 20dBs in addition to the desired user. The powers of the interferers are given with respect to the desired user. The SNR after dispreading is 10dB. BER is calculated for 1000 simulations at the intervals of two iterations as shown in Fig. 4.7. The performance of an ideal MMSE detector operating under identical conditions is also given for comparison.

![Fig. 4.7 Performance of MOE-RLS and ideal MMSE](image)

4.7 MINIMUM VARIANCE RECEivers

Here we are assessing the performance of minimum variance receivers proposed by Tsatsanis [22]. In the simulations we have four interferers at various
power levels from 4 to 10 dBs relative to the desired user. The desired user has two paths. The performance measure compared is, SINR of the receiver proposed by Tsatsanis and the ideal MMSE receiver. It can be seen from Fig. 4.8, that at low SNRs, the performance of the receiver by Tsatsanis is inferior to the ideal MMSE receiver. As the SNR improves the performance of this receiver approaches that of the ideal receiver. Equations (3.58) and (3.65) are used for calculating $\text{SINR}_{\text{Database}}$ and $\text{SINR}_{\text{Ts}}$, respectively.

![Figure 4.8 Tsatsanis receiver and ideal MMSE receiver](image)

**4.8 SUBSPACE METHODS**

**4.8.1 Batch method**

Based on signal subspace estimation, both the decorrelating detector and the linear MMSE detector can be obtained blindly, as explained in sec. 3.3.2. Fig. 4.9
compares the performance of such a blind MMSE detector and the ideal MMSE
detector. The number of users is 6 and the subspace parameters are derived from a
batch of 120 data samples. The received data is subjected to SVD to identify the
subspace parameters. The amplitude of the interferers varies from 0 to 20dB. The
signature code used is gold code of length 31. The performance of the subspace
method is inferior to the ideal MMSE detector, because in the former subspace
parameters are derived from the noisy, received signal.

Fig. 4.9 MMSE receiver using subspace method and ideal MMSE.

4.8.2 Subspace-tracking

Modern subspace tracking algorithms are recursive in nature and update the
subspace in a sample-by-sample fashion. Various subspace-tracking algorithms exist
in literature. Here we adopt the recently proposed projection approximation subspace
tracking by deflation (PASTd) algorithm, as explained in Sec. 3.3.3. The advantages of this algorithm include almost sure global convergence to the signal eigen vectors and eigen values and low computational complexity of $O(NK)$, when compared to the RLS version of the MOE blind adaptive detector.

It assumes a synchronous CDMA system with processing gain 31 and six users. The desired user is the first user. The amplitudes of the five interferers vary from 0 to 20dB. The forgetting factor used is 0.997 and the input SNR is 10dB. The performance measure is BER Vs the number of iteration of the subspace-tracking algorithm and is shown as solid line in Fig. 4.10. The BER is averaged over 1000 simulations each with 10 iterations. It can be seen that BER is high initially and comes down after some 120x10 iterations. Even after this stage, fluctuation in BER is observed. For comparison, the performance of an ideal MMSE detector, working under identical conditions is also shown in dotted lines.

![Fig. 4.10 Subspace tracking method and ideal MMSE](image)
4.8.3 Channel estimation

When the signal is transmitted over a multipath channel, at the receiver end, the effective signature waveform is the multipath channel response to the original signature waveform. Subspace-based batch methods have been proposed for blind multipath channel estimation and blind, effective signature code estimation [16]. This is explained in sec. 3.3.1.

A blind channel estimation scheme was conducted for two users when each user has two paths. Here we are making use of the fact that signal subspace is orthogonal to the noise subspace. Once we estimate the channel response, the effective signature code can be estimated, which in turn can be used in subspace-based algorithms to identify the decorrelating or MMSE detector. An adaptive channel estimation scheme is proposed in [15], which can be coupled with subspace tracking algorithms to get a blind adaptive channel estimation and data detection scheme in a multipath scenario.

4.9 CONCLUSION

This chapter gives the implementation issues of the basic detectors like conventional matched filter, decorrelator and MMSE detectors. It can be seen from the figures that these basic detectors are behaving as expected. The data-aided MMSE and ideal MMSE are compared and no perceptible differences were observed. The performance of the DMI-MMSE detector was then verified to be inferior to the ideal MMSE receiver, probably because the autocorrelation matrix was derived from the received signal itself. An MOE detector using LMS and RLS algorithm was then tested. It can be seen that MOE-LMS detector outperforms the
MOE-RLS detector. Subspace method in batch mode and in tracking mode also was experimented. It was seen that, in addition to its increased computational complexity, subspace-tracking algorithm fails to deliver reliable results. In the next chapter we discuss the proposed detector.