A Study of Designing of Multi-Carrier CDMA System with Multi-Detector based on DGT

Hyung-Yun Kong[1], Kwang-Chun Ho[2]

[1] School of Electrical Engineering and Automation, University of Ulsan
San 29, MuGeo-Dong, Nam-Gu, Ulsan City, Korea, 680-749
Phone: +82-52-259-2194, Fax: +82-52-259-1686,
hkong@uou.ulsan.ac.kr

[3] Department of Information and Communications, Hansung University
389, Samsun-Dong 2-Ga, Sungbuk-Gu, Seoul 136-792, Korea
Phone : +82-2-760-4253, FAX : +82-2-760-4435
kwangho@hansung.ac.kr

Abstract: In this paper, we introduce the MC-CDMA (Multi-Carrier CDMA) system with MD (multi-detector). Due to unknown functional form of noise in wireless channel environments, it is not easy to design the detector through estimating the functional form of noise. Instead, we design the MD, which is constructed based on DGT (Data Grouping Technique) and quantiles estimated through RMSA (Robbins-Monro Stochastic Approximation) algorithm.

1. Introduction

The MC-CDMA, which is a form of combining DS-CDMA and OFDM (Orthogonal Frequency Division Multiplexing), is a promising technique for achieving the high data rate applications [1]. Recently, the performances of the MC-CDMA system employing various equalization or detectors technique, including diversity combining techniques, have been studied [2]. In many wireless communication environments frequency selectivity caused by multi-path propagation degrades the performance of digital communication channels by causing ISI with imposes limitations of the data transmission rate. In general, communication systems, in particular, must operate in a crowded electro-magnetic environment where in-band undesired the receiver treat signals as noise. These interfering signals are often random, but not Gaussian. However, in most practical situations, the channel characteristics are not known beforehand, so the assumption of a Gaussian environment will lead to poor detector and equalizer designs. In this paper, we use the theory of m-interval detectors to design MD and assume that the detected symbols are correct. From the training and transmitting mode, we can observe the pure noise, which is equiprobably partitioned into finite number of independent regions based on DGT and quantiles estimated by RMSA algorithm. In section II, we introduce the basic RMSA (*Robbins-Monro Stochastic Approximation*) algorithm and DGT. The proposed MD based on DGT will be presented in section III, and section IV and V show the results of simulation & conclusion.

2. Quantiles, Partition Moments & DG

2-1. Quantiles & Partition Moments

In this section, we present the basic RMSA algorithm briefly, and begin with the scalar case first. We assume that the R.Vs $\{r_n\}$ have a common distribution function $F(r)$ that is strictly increasing on the interval $-\infty < \kappa_0 < \kappa_n < \infty$, and that $F(\kappa_0) = 0$, $F(\kappa_n) = 1$.

We seek an estimate of the quantiles κ that satisfies

$$P_r[r_n < \kappa] = F(\kappa) = p \qquad (1)$$

for given value of *p*. The available data is the sequence $\{r_n\}$, for $n = 0,1,2,\Lambda$.

The proposed recursive estimation is, for $n = 0,1,2,\Lambda$

$$v_{n+1} = v_n - g_n[u(v_{nn} - r_{n+1}) - p] \qquad (2)$$

where $u(\cdot)$ is the *Heaviside stepfunction.*

$$u(x) = \begin{cases} 1 & , \quad x \geq 0 \\ 0 & , elsewhere \end{cases} \qquad (3)$$

and $\{g_n\}$ is the sequence of positive numbers having the following conditions:

$$g_n \Downarrow 0, n \Rightarrow \infty , \quad \sum_{n=0}^{\infty} g_n = \infty, \quad \sum_{n=0}^{\infty} g^2{}_n < \infty, \quad (4)$$

We define partition moments by

$$m_i(c,d] = E[\chi_{(a,b]}(r)r^i], \quad i = 1,2,\Lambda ,\text{n} \qquad (5)$$

where $\chi_{(c,d]}$ is the indicator function of the interval $(c,d]$ that is a subset of the interval $(a,b]$.

From the available sequence $\{r_n\}$, the proposed partition moments estimators are

$$W_{n+1} = W_n + g_n[H_{n+1} - W_n] \qquad (6)$$

where $H_{n+1} = \chi_{(a,b]}(r)r^l$ and g_n satisfies the previous conditions described.

We deal with data-blocks that are *(m+1)*-dimensional vectors. As a first step, we replace the conditioning vector $(r_n, r_{n-1}, \ldots, r_{n-m})$ by the output of a DGT. The DGT maps from R^{m+1} to $\psi = \{q_0, q_1, \ldots, q_t\}$, where *D* is a finite set with elements called pseudo-states of $(r_n, r_{n-1}, \ldots, r_{n-m})$. The mapping is defined as follows: Let the space R^{m+1} be partitioned into

$$\psi : R^{m+1} = Y_{i=1}^{t} R_i, \quad R_i \ I \ R_j = \phi, \ i \neq j \quad (7)$$

then DGT $(r_n, r_{n-1}, \ldots, r_{n-m}) = d_i$

$$\text{if } (r_n, r_{n-1}, \ldots, r_{n-m}) \in R_i \quad (8)$$

2-2. DGT (Data Grouping Technique)

The sample space should be equiprobably partitioned because the equiprobable partitioning retains the maximum amount of information about the original random variables. First, the present sample r_n is eqiprobably partitioned by estimated quantiles η_k. The first component is quantized by 'T' levels as follows;

$$
\begin{aligned}
\Psi_0 : \quad & r_n < \eta_1 \text{ -----> } D_0(r_n) = 0 \\
& \eta_1 \le r_n < \eta_2 \text{ -----> } D_0(r_n) = 1 \\
& \quad \text{M} \\
& \quad \text{M} \\
& \eta_{T-2} \le r_n < \eta_{T-1} \text{ -----> } D_0(r_n) = T-2 \\
& r_n \ge \eta_{T-1} \text{ -----> } D_0(r_n) = T-1
\end{aligned}
\quad (9)
$$

Next, for each substream $\{r_{n-1} \mid D_0(r_n) = i\}$ where $i = 0, \ldots, T-1$, the second component will be partitioned with equal probability using Eq (2) and quantized by 'L' levels.

Under $D_0(r_n) = i$

$$
\begin{aligned}
\Psi_1 : \quad & r_{n-1} < \mu^1_{1,j} \text{ -----> } D_1(r_n, r_{n-1}) = \delta_{i,0} \\
& \mu^1_{1,j} \le r_{n-1} < \mu^1_{2,i} \text{ -----> } D_1(r_n, r_{n-1}) = \delta_{i,1} \\
& \quad \text{M} \\
& \mu^1_{Y-2,j} \le r_{n-1} < \mu^1_{Y-1,j} \text{ -----> } D_1(r_n, r_{n-1}) = \delta_{i,Y-2} \\
& r_{n-1} \ge \mu^1_{Y-1,j} \text{ -----> } D_1(r_n, r_{n-1}) = \delta_{i,Y-1}
\end{aligned}
\quad (10)
$$

where

$$
\begin{aligned}
& 0 \le \delta_{n,m} \le T \times L - 1 \\
& n = 0, \ldots, T-1 \\
& m = 0, \ldots Y-1
\end{aligned}
$$

Again, each substream $\{r_{n-2} \mid D_1(r_{n-1}, r_n)\}$ will be treated using a similar procedure as shown above for each $D_1(r_n, r_{n-1}) = \delta_{n,m}$. After iterating the above procedures, the final partition D_m quantizes the vector $(r_n, r_{n-1}, \ldots r_{n-m})$ into equiprobable *(m+1)*-tuple outputs $q_0, q_1, \ldots, q_l$, where $l = T□L^m - 1$, assuming that r_n is partitioned by the 'T' level and r_{n-1}'s are partitioned by the 'L' level.

3. MC-CDMA System with Multi-Detector

3-1. Basic MC-CDMA System

MC-CDMA system addresses the issue of how to spread the signal bandwidth without increasing the adverse effects of the delay spread, which is a measure of the length of the channel impulse response. With MC-CDMA, a data symbol is transmitted over *N* narrowband sub-carriers where each sub-carrier is modulated by "1" or "0" based on a spreading code. Different users transmit over the same set of sub-carriers but with a spreading code that is orthogonal to the codes of other users. The transmitted signal corresponding to the *k-th* data bit of the *m-th* user is

$$s_{mc}(t) = \sum_{i=0}^{N-1} c_m[i] a_m[k] \cos(2\pi f_c t + 2\pi i \frac{F}{T_b} t) p_{T_b}(t - kT_b) \quad ,$$

$$c_m[i] \in -1, 1 \quad (11)$$

where, $c_m[i]$ represents the spreading code of the *m-th* user and $p_{T_b}(t)$ is defined to be an unit amplitude pulse that is the interval of $[0, T_b]$.

And, receive signal is

$$r(t) = \sum_{m=0}^{M-1} \sum_{i=0}^{N-1} \rho_{m,i} c_m[i] a_m[k] \cos(2\pi f_c t + 2\pi i \frac{F}{T_b} t + \theta_{m,i}) + n(t) \quad (12)$$

where, the effects of the channel have been included in $\rho_{m,i}$, $\theta_{m,i}$ and $n(t)$ is noise component s. To simplify the analysis, it is assumed that exact synchronization with the desired user is possible. The first step in obtaining the decision variable involves demodulating each of sub-carriers of the received signal, and despreading by chip code having the length of *N* then each output data pass through the multi-detector to yield decision.

3-2. Proposed Multi-Detector based on DGT

In this section, we consider and design the MD which is based on DGT. First, *m*-dimensional noise sample space is equiprobably partitioned into a finite number of regions [3], using DGT and quantiles and based on training sequences. Subsequently, under each hypothesis and equiprobably partitioned cells of past noise samples, the received signals are grouped. In this procedure, partitioning signal part is not involved. The detected signal is reliable when *SNR* is relatively high. In this paper, it is defined as *SNR >0*. Therefore, we can observe pure noise samples during training and transmitting mode, assuming the detected symbols are correct. After obtaining pure noise samples from $n_{n-k} = r_{n-k} - a_{n-k}$ (i.e., r_{n-k}: received signal, a_{n-k} : known signal/ detected signal), we replace the conditioning vector $(n_n, n_{n-1}, \cdots, n_{n-r})$ by the output of a DGT.

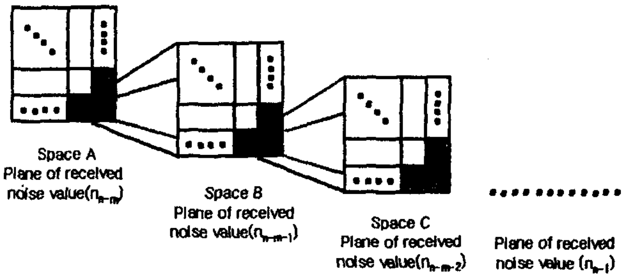

Figure 1 : Partition Procedure

First, noise sample n_{n-m} is partitioned continuing the process until noise sample n_{n-1} is partitioned (see Fig.1). The received signals will be grouped according to hypothesis which is based on carrier phase and equiprobably partitioned parts of past noise samples.

The threshold under each partition and each hypothesis can be obtained by following functions;

$$P_1 + P_0 = 1 \qquad (13)$$

where P_0 is P(received data $= 0$),

P_1 is P(received data $= 1$), ρ presents the estimated quantile

4. Simulation Results

We use the training mode, using 1,000,000 data, to set up the value of threshold in each partitioned sample space, and the 6th order *Chebychev* filter, as a transmitting filter is used to generate ISI, which consists of three past information affecting the present data. A total number of partition is 100, using the previous three noise sample.

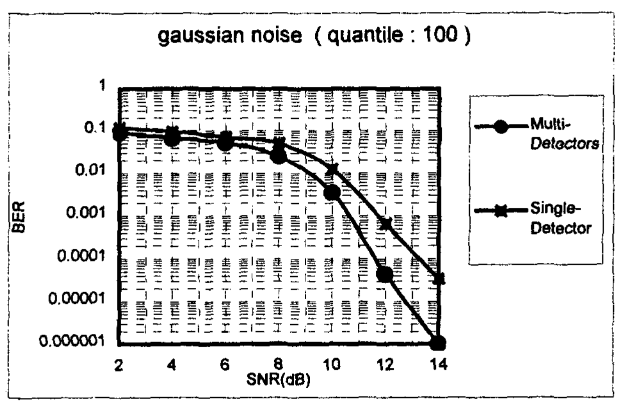

Figure 2 : Comparison of Performance under gaussian noise channel environment

Fig.2 shows the comparison of performance under 100 partition levels and shows that the system we proposed produces better performance about 1~1.5dB at BER 10^{-5}.

To apply the MD system to typical WLANs and show the performance of suggested system, we use MD system instead of single detector system in IEEE 802.11b WLAN.

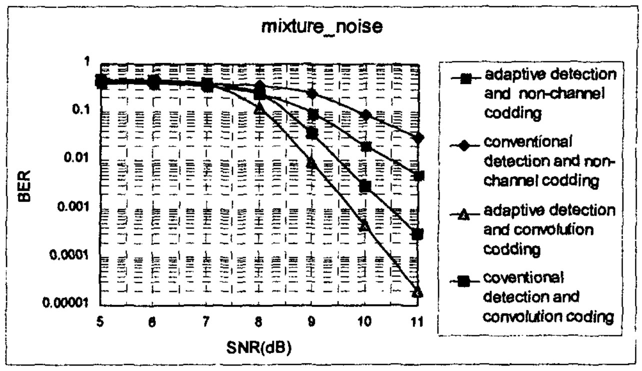

Figure.3 : Performance comparison in IEEE 802.11b WLAN under non-gaussain noise channel environment

Fig.3 shows the performance of WLANs with MD system along with convolutional coding under two different channel environment, and the improvement performance in terms of *BER* is from 0.5 to 1dB, as compared to single sample detector.

5. Conclusion

In this paper, we use the partitioning sample space to design a multi-detector being able to apply to MC-CDMA system. We use 3-dimensional noise sample space, different number of partition levels to set up the multi-detector. This system produces better performance when comparing to single detector system and the reason is that the output signal after demodulator passes through a multi-detector, which is susceptible to detection errors while other has a single sample detector. The performance will be improved as increasing the partition level until the saturation point is reached.

References

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