Scientific Journal Impact Factor (SJIF): 3.518
International Journal of Modern Trends in Engineering and Research
ISSN (ONLINE) : 2349 - 9745 ISSN (PRINT) : 2393 - 8161

Neural Network Based Partial Parallel Interference Cancellation Multiuser Detection Using Hebb Learning Rule

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Abstract - In CDMA communication systems, in order to decrease the influence on reception performance resulted from incorrect decision of the interference users' information bits in parallel interference cancellation (PIC) process, a recurrent neural network based on Hebb learning rule is designed and applied to adjusting interference cancellation factors (ICF) in partial parallel interference cancellation (PPIC) multiuser detection. Simulation results show that the proposed Hebb-PPIC detection has strong anti-MAI ability and its performance of bit error rate (BER) is improved on the basis of conventional PIC in both conditions of ideal power control and "near-far" scenario.

Key words - PIC, Hebb learning rule, ICF, PPIC, BER, MAI

I. INTRODUCTION

Multi user detection (MUD) is a technology that spawned in the early 80's. It has now developed into an important full-fledged field in communication system where simultaneously occurring digital streams of information interfere with each other. Conventional detectors based on the matched filter just treat the MAI as additive white Gaussian noise (AWGN). However, unlike AWGN, MAI has a nice correlative structure that is quantified by the cross correlation matrix of the signature sequences. Hence, detectors that take into account this correlation would perform better than the conventional matched filter bank. MUD is basically the design of signal processing algorithms that run in the black box shown in figure 1. These algorithms take into account the correlative structure of the MAI.

A. Linear Multiuser Detectors

The matched filter bank detector was the conventional and simplest way of demodulation CDMA signals (or any other set of mutually interfering digital streams). The matched filter also forms the front end in most MUD's and hence understanding the operation is crucial in appreciating the evolution of MUD technology [2].

In conventional single user digital communication systems, the matched filter is used to generate sufficient statistics for single detection. In the case of a multi- user system, the detector consists of a bank of matched filters(each matched to the signature waveforms of different users in the case of CDMA). This is shown in figure 6 this type of detector is referred to as conventional detector in MUD literature. It is worth mentioning that we need exact knowledge of the users signature sequences and the signal timing in order to implement this detector.

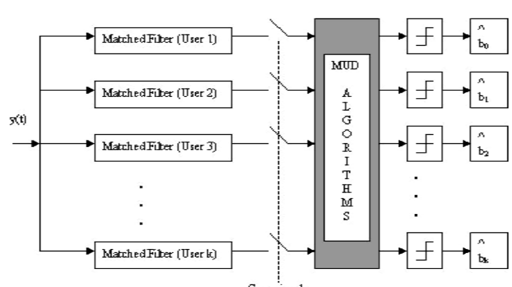

Figure 1: A typical Multiuser Detection

The decision statistic at the output of the k[th] - matched filter is given by $y_k = \int_0^T y(t)s_k(t)dt$

B. Non Linear Multiuser Detectors

We encountered the technique of successive cancellation (also known as stripping or successive decoding). This approach is based on a simple and natural idea: if a decision has been made about an interfering user's bit then that interfering signal can be recreated at the receiver and subtracted from the received waveform. This will cancel the interfering signal provided that the decision was correct: otherwise it will double the contribution of the interferer. Once the subtraction has taken place , the receiver takes the optimistic view that the resulting signal contains one fewer user and the process can be repeated with another interferer, until all but one user have been demodulated. In order to fully describe the receiver we just need to specify how the intermediate decisions are obtained. In its simplest form, successive cancellation uses decisions produced by single user matched filter, which neglect the presence of interference. Since erroneous intermediate decisions, the order in which users are demodulated affects performance [3].

A popular approach is to demodulate the user in the order of decreasing received power. However, this is not necessarily best since it fails to take into account the cross correlations among users. A sensible alternative is to order users according to

$$E\left[(\int_0^T y(t)s_k\,(t)dt)^2\right]= \sigma^2 + \; A_k^2 + \sum_{j\neq k} A_k^2\rho_{jk}^2$$

which can be estimated easily from the matched filter outputs.

C. Signal Model

The K- user discrete time basic synchronous CDMA model has been used throughout the development of the paper. The case of antipodally modulated user information (BPSK modulation) spread using BPSK spreading is considered [1]. To make the paper reliable in the time allocated, a very small spreading sequence of length 31 was used. A preferred pair [1, 2] of m- sequence generated by the primitive polynomials <45>and <75> were used for all the 2- user scenarios. For the number of users greater than 2, gold codes generated by the 2 m-sequences described above were used. Unless otherwise mentioned, in all the simulations perfect power control is assumed i.e., the receiver amplitudes of all the users are assumed to be the same. The signal at the receiver is given by

$$y(t) = \sum_{j=1}^{k} A_k b_k s_k(t) + \; n(t)$$

Where s_k is the signature waveform of the k[th] user (s_k is normalized to a unit energy i.e. $< s_k, s_k >=1$). For BPSK spreading with an m- sequence of length 31, the signature waveform is defined as

$$s_k(t) = \sum_{k=0}^{30} a_k p_T\,(t\; - kT_c)$$

Where T = bit period, T_c = chip interval,
a_k is the normalized spreading sequence.
b_k is the input bit of the k[th] user, $b_k \in\{-1,1\}$.
A_k is the received amplitude of k[th] user.
$n(t)$ is the white Gaussian noise with power spectral density N_o.
Since synchronous CDMA is considered, it is assumed that the receiver has some means of achieving perfect chip synchronization. In matrix notation (1,1) can be written as

$$y = SAb + n$$

The cross correlation of the signature sequence are defined a

$$\rho_{ij} = < s_i, s_j >= \sum_{k=1}^{N} s_i\,(k)s_j(k)$$

Where N is the length of the signature sequences (31 in our case).

The cross correlation matrix is then defined as

$$R = \begin{bmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1k} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2k} \\ \vdots & \vdots & \cdots & \vdots \\ \rho_{k1} & \rho_{k2} & \cdots & \rho_{kk} \end{bmatrix}$$

R is a symmetric matrix, non negative, toeplitz matrix.

II. The Proposed Technique

A. Hebb Learning Rule

Hebb learning rule is one of the neural network learning rules widely used. It was proposed by Donald Hebb in 1949 as a potential mechanism for the brain to adjust its neuron synapse and from then on it has been used in training artificial neural network. Hebb learning rule is based on Hebb assumption when an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased [5]. Hebb assumption means that if a positive input pj results in a positive output a_i, w_{ij} should be increased, which is a kind of mathematics explanation for it, i.e.,

$$w_{ij}^{new}=w_{ij}^{old}+\alpha f_i(a_{iq})g_j(p_{jq})$$

also simplified as

$$w_{ij}^{new}=w_{ij}^{old}+\alpha a_{iq}p_{jq}$$

where p_{jq} is the j^{th} element of the q^{th} input vector p_q, a_{iq} is the i^{th} element of network output when the q^{th} input vector is entered into the network and alpha is a positive constant called as learning rate. It should be noticed that based on Hebb assumption can be expanded as follows: the variation of weights is proportional to the product of active values from each side of synapse. Therefore, weights will increase not only when p_j and a_i are both positive but also when they are both negative. Besides, Hebb rule will decrease weights as long as p_j and a_i have opposite signs.

B. Hebb-Partial Parallel Interference Cancellation (PPIC) Model

The decision variable at stage 1 (output of MF) in conventional PIC is

$$r_i^{(1)}=A_ib_i+\sum\rho_{ik}A_kb_k+n_i \quad ,i=1,\ldots.K,$$

where ρ_{ik} is the correlation coefficient between spreading codes of the i^{th} user and kth user. The output after decision is

$$b_i^{(1)}=sgn[r_i^{(1)}] \quad ,i=1,\ldots..K$$

The decision variables of the following stages (interference cancellation stages) are

$$r_i^{(m)}=A_ib_i+\sum\rho_{ik}A_k\ (b_k-b_k^{\wedge(m-1)})+n_i \quad ,i=1,\ldots.K,$$

and the corresponding decision outputs are

$$b_i^{(m)}=sgn[r_i^{(m)}] \quad ,i=1,\ldots..K$$

The decision variables at interference cancellation stages in PPIC with ICF are

$$r_i^{(m)}=A_ib_i+\sum\rho_{ik}A_k(b_k-w_i^{(m)}b_k^{\wedge(m-1)})+n_i,i=1,..K,\ m=2,3,..$$

where $w_i^{(m)}$ is the ICF of the ith user at stage m. Apply recurrent neural network based on Hebb learning rule to adjusting $w_i^{(m)}$

$$w_i^{(m)}=satlin\{w_i^{(m)}[1+\tau(1-|b_i^{\wedge(m-1)}-b_i|)]\}$$

where $w_i^{(1)}=1$, i =1,…,K , $\tau=(0,1)$ is the learning rate and saturated linear function satlin is used to assure the convergence of learning process [6]. According to the theory above Hebb-PPIC receiver is designed whose structure is presented below.

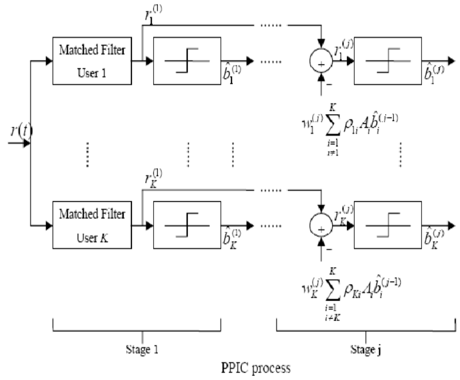

Figure 2: Block Diagram of Partial Parallel Interference Cancellation Receiver

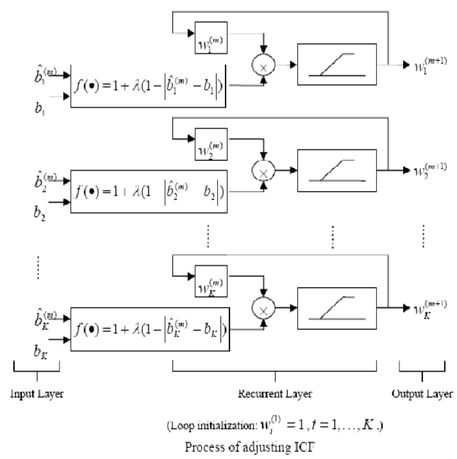

Figure 3: Partial Parallel Interference Cancellation Receiver with Hebb Learning rule

III. Simulation Results

Based on the above analysis computer simulation drawn on BER Performance of PPIC Receiver using Hebb Learning Rule and Comparison of Hebb PPIC with other Detectors has been observed.

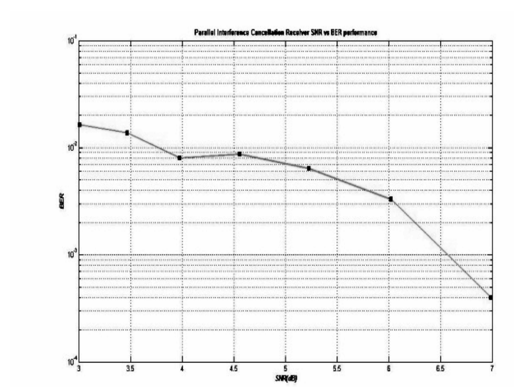

Figure 4: BER Performances of Parallel Interference Cancellation (PIC) Receivers

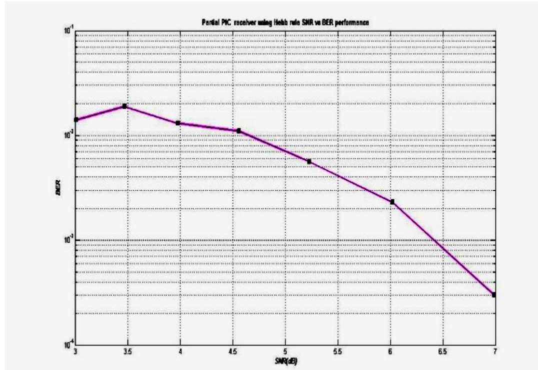

Figure 5: BER Performances of Partial Parallel Interference Cancellation (PPIC) Receivers

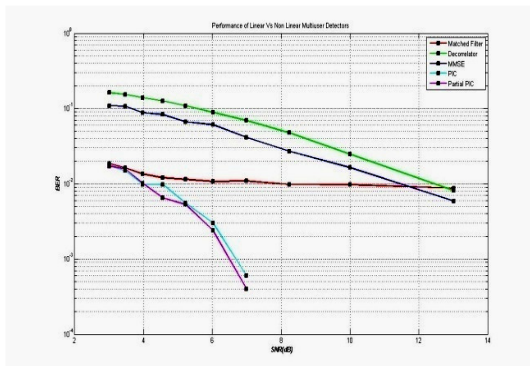

Figure 6: BER Performances of Linear Vs Non Linear Multiuser Detectors

From the above simulation we can observe that figure 4 shows the Bit Error Rate (BER) of PIC Receivers. Figure 5 shows the Bit Error Rate (BER) of PPIC Receivers using Hebb Learning rule. Figure 6 gives the Bit Error Rate (BER) performance of Linear detectors like Matched Filter, Decorrelating Detector and MMSE detector vs. PIC and PPIC. The simulation shows that the Hebb-PPIC receiver is giving the Lowest BER at the lower SNR level itself than the other detectors.

IV. Conclusion

Spread spectrum is useful in reducing the interference and having the Anti-jamming capability it can be used in the various modern technologies where the security is a concern. So the same concept is used in the CDMA where the codes allocated to the users are generated Direct Sequence Spread Spectrum Technique. As our paper deals with the Gold Codes there are also different codes like Walsh codes and OVSF codes which open another perspective of the paper. We are dealing with both the Linear and Non Linear Multiuser Detectors or Receivers which are good at their individual performances but there will be some tradeoffs in each receiver that can be overcome by others. We observed some of the receivers' performance in order to obtain the optimized Bit Error Rate. We observed that the Parallel Interference Cancellation Receiver and Partial Parallel Interference Cancellation Receiver will produce an optimized Bit Error Rate. Our paper mainly deals only with Synchronous case so it also can be extended to Asynchronous. .The same concept can be extended to like W-CDMA and MC-CDMA technologies because they are simply applications of the Spread Spectrum Technology. Our Paper will have a great perspective in the future technologies and we keep trying to extend these concepts and enhance our knowledge.

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