Multi-User Detection for CDMA communications based on self organized neural networks structures

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Abstract

In the upcoming high transmission rate system, based on code division multiple access, standard multi-user detection methods are restricted because of performance and implementation complexity issues. To end up with this issue, self-organized neural networks are proposed. An optimal multi-user detector can be implemented, by using Growing Grid network.

1. Introduction

Future wireless applications will require very high data rates and high quality of service. The communication channel has to be shared in an efficient manner. An interesting technique is based on spread spectrum and orthogonal coding sequences : Code Division Multiple Access (CDMA).

CDMA is a promising technique for radio access in a variety of cellular mobile. CDMA transmission systems has been chosen as a multiple access technique for the recent American (IS-95) and European (UMTS) portable radio norms.

2. Multi-users detection in CDMA receiver

Spread spectrum [1] is an easy-to-use solution for channel optimization. The bandwidth of the transmitted signal is larger than the initial user's bandwidth. Spreading is performed by the multiplication of the original signal with a spreading code which gives it specific characteristics alike to noise. Spread spectrum signals are almost unaffected by interferences due to the same kind signal because of the proper intercorrelation characteristics of the sequences.

When working with CDMA, a unique coding sequence is allocated to each user, which is not related with all the other codes. In the case of synchronized transmissions system, optimal performances appear with the use of orthogonal sequences like, for instance, Walsh-Hadamard sequences. CDMA can be performed both in time and frequency domain:

- Direct Sequence CDMA transmissions.
  Each data symbol $s_j(t)$ is multiplied by all the sequence C_j, assigned to user j. The chip rate R_c is much higher than the data user rate R_s and is given by $R_c = L.R_s$. The spreading operation is applied in the time domain. The transmitted power is reduced by L and the resulting signal looks like noise.
- Multi-carrier CDMA transmissions [2].
  Each data symbol $s_j(t)$ is transmitted in parallel over N_c subcarriers, each multiplied by one code chip $C_{k,j}$, with $k = [0...N_c - 1]$. The spreading is performed in the frequency domain, and adapted to the frequency selective behavior of the channel. Furthermore, the MC-CDMA receiver employs all the received signal energy spread in the frequency domain.

2.1. Conventional / Linear detectors

In the receiver, in order to demodulate the signal, the inherent channel noise must be suppressed. The noise is modeled as an additive Gaussian noise with Multiple Access Interferences (MAI).

A Conventional Detector (CD) can recover the information by passing the received signal through a bank of filters matched to the user's signature waveforms. Detection is performed symbol by symbol.

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Conventional detector (Linear) has a very simple structure but let appears two main drawbacks. One of the major limitation of it is that it is not near-far resistant, ie, its performances degrade when powers of the other users are dissimilar. Furthermore, the number of filters to implement is directly linked to the number of users.

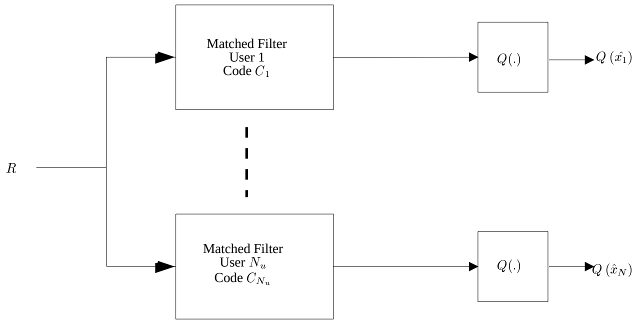

Figure 1. Conventionnal receiver.

2.2. Interference Cancellation Detectors

The aim of Interference Cancellation (IC) Detectors [2] is to evaluate the MAI part generated by users and to subtract it from the received signal. Generally, in order to improve the final decision, the detectors are cascaded, the output of detector n is applied to the entry of detector of $n+1$.

There are two major types of Multi-User (MU) detectors based on the IC: the serial interference cancellation (SIC) and the parallel interference cancellation (PIC). The aim of these IC detectors is to estimate the contribution of each user in the MAI terms and to suppress it.

The SIC detector first detects the most powerful interfering user and then cancels its contribution from the received signal. Then, the second one is cancelled and so on. The iterative process may be repeated for a few or for all users, commonly only the strongest interferers. The resulting signal is finally despread. As one supplementary stage leads to an additive time delay, a tradeoff between complexity and acceptable performances has to be found.

The PIC detector is based on the estimation of the total interference due to the simultaneous other users, in order to remove it from the received signal. All the interfering users are cancelled in parallel, reducing the time delay of a SIC detector.

The performances of the IC detectors are based on the channel estimation, which are assumed to be perfect. So, a linear detector has to be used rather than a conventional detector to improve performances.

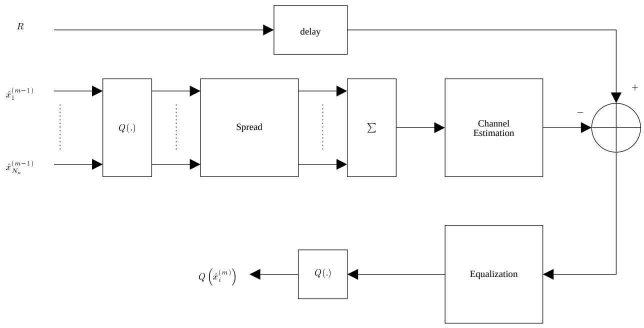

Figure 2. PIC receiver for N_u users.

2.3. Numericals Results

The results have been obtains for $N_u = 16$ users. The length of the spreading Walsh-Hadamard codes is $L_c = 16$ and $N_p = 16$, number of channels for the MC-CDMA.

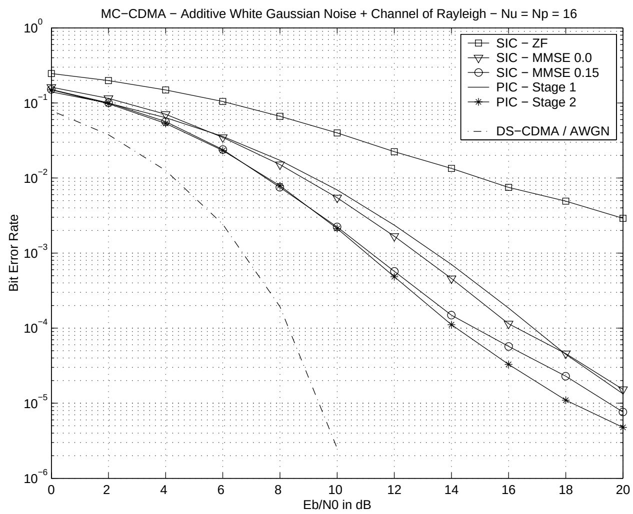

Figure 3. MC-CDMA / AWGN + Rayleigh and DS-CDMA / AWGN.

The SIC and PIC detectors achieve better performances than CD detectors. However, their complexity grows with the number of users and they are not easily reconfigurable. The PIC detector is more complex than the SIC detector.

The proposed neural networks will have to reach these performances, while keeping implementation as simple as possible with the use of regular circuit components. Results presented in figure [3] make up our comparison references.

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3. Neural Networks

3.1. Supervised Neural Networks

In a supervised neural network, the system tries to converge towards a reference behaviour (theoretical output). Generally, supervised training algorithms are based on a gradient descent algorithm.

The concept of this enhancement is to find out the solution and decreases error number [3].

- Neuron Models.
  A neural network consists of a large number of non-linear processing units : the neurons. The neuron is composed of three basic elements : a set of synapses or connecting links with weigths W_k , an adder for summing the inputs signals X_k and an activation function Q for limiting the amplitude of the output of a neuron y_k.

$$v_k = \sum_{j=0}^{m} W_{k,m} * X_j$$

$$y_k = Q(v_k)$$

- Multi-Layers Networks.
  In these nets, neurons are ordered in consecutive layers, in the following way : one input layer, one or more hidden layers and one output layer. The input vectors are propagated from the input layer to the output layer through one or more hidden layers. Each neuron receives signals only from the previous layer and transmits its outputs them to the next one. Final outputs are compared to expected answers : it is a supervised training because the answer awaited is known.

- Hopfield Networks.
  The Hopfield network is the best known dynamic network model. It is a single layer network with complete interconnections between neurons. Each one sends and receives signals to and from all the other neurons of the network, included itself.

Supervised neural nets have been used and optimized in CDMA system. However, a large number of neurons is required to maintain the prediction accuracy and increases complexity. Furthermore, if the number of users changes, a re-learning step is necessary.

3.2. Unsupervised Neural Networks

Unsupervised neural networks give to the network a stereotyped behaviour within their environment. In a self organized network, representative data or specific characteristics (characteristics of input data) are founded, just by looking at various entries and their resemblance's or their differences without the help of a supervisor.

3.2.1 Kohonen Netwoks

The models of self-organizing neural networks, which were first introduced by Willshaw & von der Malsburg (1976) and then by Kohonen (1982)[4], allow to represent in low dimension inputs data given in high dimension. The most famous model is Kohonen map.

Kohonen networks are often used in classification problems, based on an unsupervised learning rule. The use of a neural network is split in two steps :

A learning phase: the weights of the connections are adjusted according to a learning rule, with regards to an internal criteria. After enough vectors has been presented, weights are updated for each node and all nodes in the neighborhood. Weights specify clusters that sample the input space and are organized such that the topology closes nodes are sensitive to inputs that are similar.

An execution phase: weights are no more modified, the aim is to find the similarity between an input vector and the nodes of the output layer.

3.2.2 Growing Grid Networks

First introduced by B. Fritzke in 1990 [5], Growing Cell and Growing Grid (GG) networks are a new model of self organizing maps. They have the same parameters than Kohonen networks ones, with in the network structure, relationships for the proximity of the winning neuron. For these kind of networks, the knowledge of the structure of the neural net has not to be specified, as it should be in Kohonen. The topology of the maps can be modified thanks to the insertion or the suppression of a neuron. As for Kohonen networks, the input signal is used, during the learning phase to update the values of the weights and the resulting map. On the contrary to Kohonen Self-Organizing Memory (KSOM), GG neural networks have model's parameters independent of the time. The direct proximity of the neurons and the weights are only updated.

3.2.3 ART Networks

ART (Adaptative Resonance Theory) is a neural network model with an evolutive architecture developped in 1987 by Carpenter and Grossberg. In ART network, training and execution steps are achieved in the same time. When in test, network adjusts to unknown entries by building new classes (adding neurons) while trying to keep unchanged information previously memorized.

3.3. Performances and resources comparison

3.3.1 Principles of Unsupervised Networks

Unsupervised neural networks are constituted by two layers: an input layer and an output layer. To illustrate how this network operates, we use a one or two dimensional map. Each neuron on the input layer is completely connected to each neuron of the output layer. In addition, the neurons on the output layer are laterally connected. In a case of a two dimensional output layer, the neurons are placed on a plan with lines and columns, also called grid. Each neuron has a connection with all or a part of all the neurons of the grid. The neuron is characterized by a weight vector which depends on the neuron position with regard to the others.

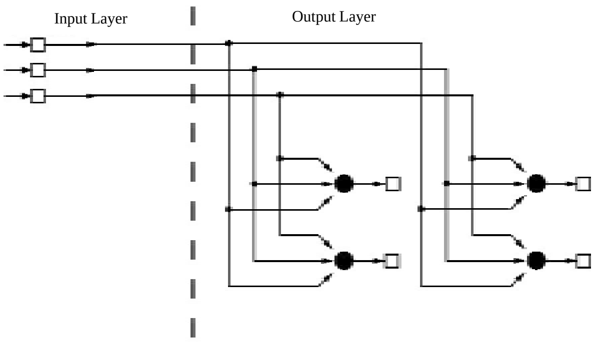

Figure 4. Neural Network in 2 dimensions.

For GG networks, the initial map is formed by four neurons. Then, neurons will be inserted or suppressed according to criteria. The maximum neurons number is one of the learning stopping cases. The input data are presented several times to the same neural network. The connections are randomly initialized with small values. Unlike the KSOM, only the direct neighborhood of the winning neuron is affected by the adaptation function.

3.3.2 Comparison of the two neural networks

In order to compare the two kind of networks KSOM and GG, we choose a set of identical evolution criteria and parameters. One of these criteria is the maximum number of neurons on the map (10x10 neurons grid for the KSOM and a maximum growth of 100 neurons for the GG). Indeed, the number of computing operations and the memory resources used depend of the number of neurons. Figure [5] show the neural networks convergence speed to a steady state. The number of iterations is reported on the x-axis, and the error percentage on the y-axis.

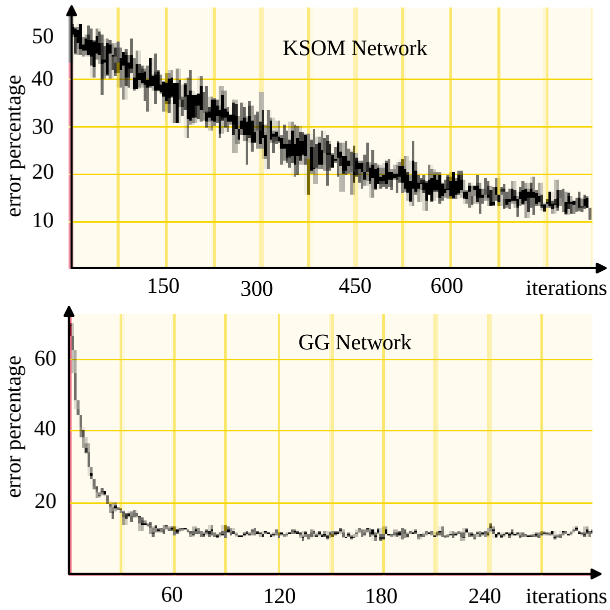

Figure 5. Neural Network Comparison.

These results show that Growing Grid neural networks are ten times more efficient and the number of operations is six times less than KSOM. ART and GG are well adapted for multi-user detection. Such neural nets have the flexibility to adapt to changing non-Gaussian environment. They are well suited for adaptive prediction, with low computational complexity.

3.4. Linking CDMA-Neural Networks

Figure [6] represents the model of the CDMA system. Orthogonal Frequency Division Multiplexing (OFDM) is performed only in the case of MC-CDMA. Preprocessing prepares the incoming data for the neural network, which replaces the multi-user detector.

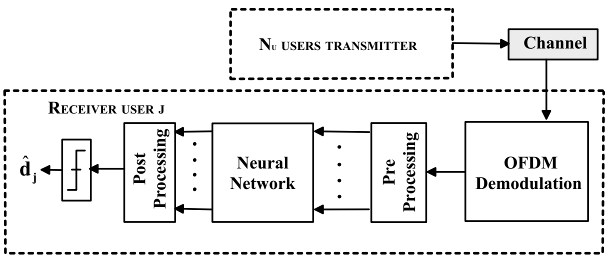

Figure 6. Neural Network Receiver

4. Description of the reconfigurable Prototyping Board

A prototyping platform will be used to implement the CDMA receiver. The board is based on a PCI motherboard from SUNDANCE MULTIPROCESSOR, where can be plugged various modules, at the TIM format (Texas Instrument Module).

This platform accepts many types of modules (DSP, FPGA, Processors CNA/CAN...). It allows fast setup and makes tests on different transmission system easier. In our study, various neuronal detectors will be implemented on a coprocessor, optimized and compared. A DSP will also be used.

4.1. DSP Module

The software module is based on a DSP TMS320C6701 from Texas Instrument. Built on a VLIW architecture, it can simultaneously process eight instructions on floating point format data. It is clocked at 167 MHz. External memories, 16MB SDRAM and 512KB SBSRAM, are also embedded. DSP C6701 will have to control and manage the whole CDMA receiver : demodulation, control, etc. It has to be optimized for great data flow transmission management.

4.2. NeuroMatrix Module

The NeuroMatrix Core [6] comprises an original 5-stage pipelined 32-bit VLIW RISC processor and a 64-bit SIMD Vector coprocessor (VCP), presented in Figure [7]. The base VCP operation is matrix by vector multiplication:

$$Y_m = U_m + \sum_{n=1}^{N} X_n * W_{n,m}$$

For instance, the execution runtime for a FFT of 1024 points is 1298 μs for a Texas Instrument C40 DSP, 460 μs for a SHARC ADSP-21061 from Analog Devices and 439 μs for a NM6403 module. NM6403 has a clockspeed at 50 MHz. Evolution is possible to 133 MHZ with NM6404.
To implement the neuronal detector in our transmission system, Neuromatrix module has been chosen. It has a specific environment for fast matrix computation.

5. conclusion

In this paper, we have presented the different Multi-User detectors for in CDMA receiver. We have detailled the existing results. After presenting results obtained with them,

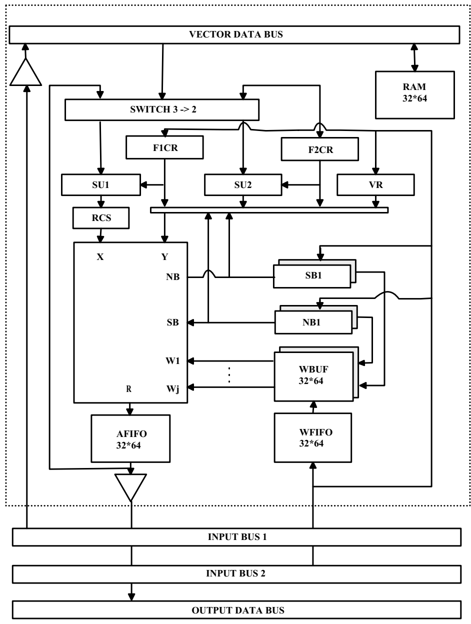

Figure 7. Vector Coprocessor Block Diagramme.

the alternative neural network solution is exposed. This unsupervised network will be implemented on a hadware platform. Thus, it is shown that the neural networks detection algorithm is a very promising multi-users detection especially for the future mobile radio systems. The association of VLIW RISC and SIMD can optimized the performance of system.

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