The International Conference on Electronics & Oil: From Theory to Applications
March 05-06, 2013, Ouargla, Algeria

An Adaptive Serial Acquisition Scheme of PN Sequence in Nonhomogenous Rayleigh Fading Channel Using Artificial Neural Networks

Sabra BENKRINAH [(1)], Malek BENSLAMA[(2)], Mourad BARKAT[(3)]

[(1)] *Kasdi Merbah Ouargla University, Genie electrical laboratory, Faculty of sciences and technology and material sciences Ouargla 30000, Algeria*

[(2)] *Mentouri Constantine University, Electronic department, Faculty of engineering sciences, Constantine 25000, Algeria*

[(3)] *King Saud University, Department of Computer Engineerin, Riyadh, KSA*

s.benkrinah@gmail.com

Abstract— **In this paper, we propose an adaptive non-coherent serial pseudo-noise (PN) acquisition scheme for code division multiple access (CDMA) communication systems. Acquisition systems based on a fixed threshold may not be able to adapt to varying mobile communication environments leading to a high false alarm rate and/or a low detection probability. Accordingly, an adaptively varying threshold scheme based on artificial neural networks, namely the artificial neural networks constant false alarm rate (ANN−CFAR) algorithm for the serial system under consideration to improve the detection performance. The performance of the proposed system in terms of probability of detection, false alarm rate and mean acquisition time in a nonhomogenous Rayleigh fading channel is studied and compared with those of the conventional adaptive acquisition scheme based on CA-CFAR and OS-CFAR detectors.**

Key-Words— serial acquisition; PN sequences; CDMA; CFAR; Rayleigh fading channel; ANNs.

I. Introduction

Pseudo-noise (PN) code synchronization is an essential task in CDMA mobile communication systems because data transmission is possible only after the spread spectrum receiver accurately synchronizes the locally generated PN code with the incoming PN one [1]. This synchronization is usually achieved in two basic steps: acquisition and tracking. The first step achieves coarse alignment within some fraction of one code chip interval between the two PN codes; while the second achieves finer alignment. In this paper, we consider the code acquisition problem [2].

Acquisition methods can be classified as serial search methods and parallel search ones, which have been extensively treated in the literature [3]. In a serial search scheme [2], each possible code phase of a given position in the uncertainty region is tested one at a time, while in a parallel search strategy [4], many, if not all, of the possible code phases are tested simultaneously. The focus of this paper is on serial search acquisition because of its hardware simplicity.

To communicate with code-division multiple-access (CDMA), a pseudo-noise (PN) code acquisition should be performed first. In conventional systems, only the structure of the acquisition system is changed to gain better performances. Since, the received signal levels are unknown and location varying, good acquisition performance of a PN sequence may not be achieved if a fixed threshold is employed. These facts suggest the use of adaptive signal processing techniques employing an adaptive detection threshold, which should be determined in accordance with the local situation [5,6].

Many constant false alarm rate (CFAR) processors used in radar systems have been also applied in code acquisition problems for estimating the variance of noise in DS/CDMA systems; namely, the cell averaging (CA) and the ordered-statistics (OS). The CA-CFAR processor is an optimum CFAR processor in homogenous environments [7]. Yet, the assumption of homogenous environment is no longer valid when the number of users changes abruptly (presence of multiple-access interference) and/or there is fading. In such situations, the performance of the CA-CFAR processor is seriously degraded [8]. Various classes of CFAR techniques have been proposed to enhance the robustness against nonhomogeneous environment for different applications [8]. In particular, OS based CFAR detectors proved to give good performance in the presence of MAI (Multiple Access Interference). The OS-CFAR detector was first proposed in [ ], in which an appropriate reference cell is used to estimate the background noise power level. The OS-CFAR detector has a small additional detection loss over the CA-CFAR detector in homogeneous backgrounds but can resolve closely spaced interferences. However, it requires a longer processing time than the CA-CFAR detector [9].

In fact, we need a detector that can give butter performance in nonhomogenous background, it must adapt with sever environment cases, that is characterized by presence of MAI (Multiple Access Interferences) and multi-path problem (Rayleigh fading), and make the best decision in small processing time. Several factors motivate us to apply Artificial Neural Networks (ANN) as a CFAR detector. Also, the random structure of MAI and nonlinear decision formed by an optimal detector in CDMA can be realized by ANNs.

This paper is organized as follows: Section 2 describes the acquisition scheme. Section 3 presents expressions for deriving detection and false alarm probabilities for CA and

OS-CFAR detectors in Rayleigh fading channel. We also explain the neural network CFAR detector used in our study. The mean acquisition time expression is also given in this section. Simulation results for the proposed system are given in Section 4 along with comparison to conventional CA and OS-CFAR detectors. Finally, we conclude this work with conclusions and some future works.

II. SYSTEM DESCRIPTION

The system under consideration is a single dwell serial search scheme with a noncoherent detection as shown in Fig.1.

This system consists of a single adaptive detector (AD) with a correlation tap size *N*. The AD consists of two blocks: the first block is the conventional noncoherent matched filter (MF) detector as shown in Fig.2. The second bloc illustrates the adaptive CFAR operation of the decision process. Fig.3 illustrates the overall operation in some details. The received PN signal plus noise and any interference are arriving at the input of the adaptive detector. If the AD declares that the present cell is the correct one, the tracking loop is activated, and the relative time delay of the local PN signal is retarded by ΔT_C, where T_C is the chip time, to examine the next cell. The whole testing procedure is repeated. Usually the value of Δ is 0.25, 0.5 or 1. In our case, Δ is set to 1. On the other hand, if the AD declares that the present cell is the noncorrect one, the phases of the two codes (incoming and local) are automatically adjusted to the next offset position and the test is repeated.

For the adaptive operation of the decision processor, the constant false alarm rate (CFAR) is used. The threshold value of the comparator in the AD is adapted in accordance with the magnitude of the incoming signals. Accordingly,

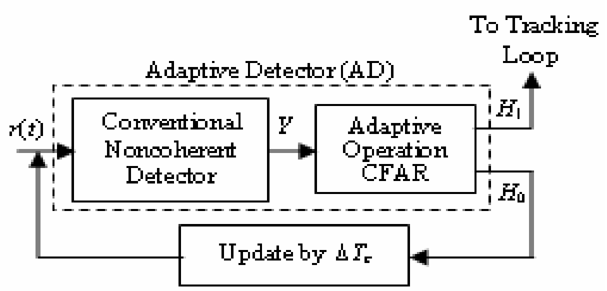

Fig.1. Adaptive serial search acquisition scheme.

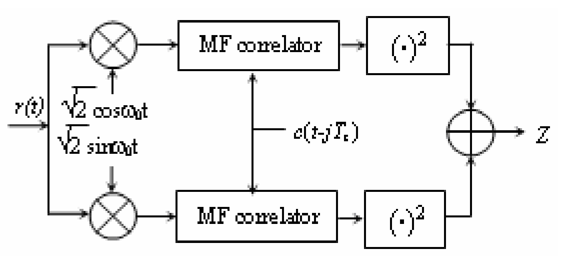

Fig.2. I-Q noncoherent matched filter.

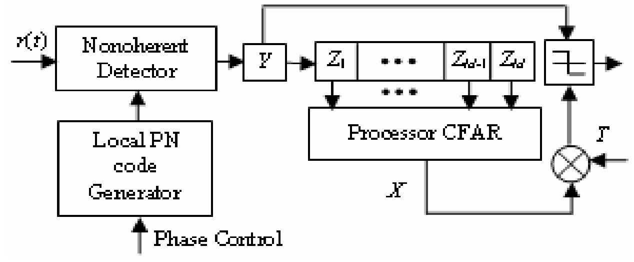

Fig.3. Bloc diagram of the adaptive detector.

the outputs of the correlator are sent serially into a shift register of length *M*+1. The first register, denoted as *Y*, stores the output of the test phase. The following *M* registers, denoted by Z_j, $j = 1, 2, \ldots, M$, and called reference window, store the output of the previous *M* phases. Using the suitable algorithm CFAR, the system can estimate the background noise power level *X* of the incoming signals. The value *X* is scaled by *T*, where *T* is set according to the desired false alarm rate from the algorithm CFAR used by the AD. Therefore, the adaptive threshold value of the adaptive detector is *TX*.

III. SYSTEM ANALYSIS

In the derivation of the detection and false alarm probabilities for a typical Rayleigh fading channel, the following assumptions are made [7]: *(i)*There is one samples corresponding to the correct phase (one H_1 cell) , *(ii)*All samples are independent, *(iii)*The correlation tap size $N >> 1$ is selected so that the correlation of the received sequence and the local code is about zero when they are not in phase (H_0 cell), *(vi)*The self noise of the desired signal due to multipath transmission and due to MAI inflected by the (*U*-1) data transmission users can be modeled by AWGN.

The communication system under consideration consists of *U* simultaneous transmitters, which includes (*U*-1) data transmission users (who have finished acquisition) and one initial synchronization user (whose PN sequence is being acquired by the base station). We assume that the first user is the initial synchronization user, whose performance to be evaluated. Each user is assigned a unique CDMA sequence, which spreads the data sequence. The received signal can then be written as

$$r(t) = \sum_{l=0}^{L-1} \sqrt{2P_R}\,\alpha_{1l}\, c_1(t-\tau_1-lT_c)\cos(2\pi f_c t+\theta_{1l}) + \sum_{k=2}^{U}\sum_{l=0}^{L-1}\sqrt{2P_I}\,\alpha_{kl}\, b_k(t-\tau_k-lT_c)c_k(t-\tau_k-lT_c) \cdot\cos(2\pi f_c t+\theta_{kl})+n(t) \qquad (1)$$

where, τ_k is the relative time delay associated with an asynchronous transmission scheme, $\theta_{kl} = \varphi_{kl} - \Psi_{kl} - 2\pi f_c(\tau_k + lT_c)$, which are modeled as independent and identically distributed (i.i.d.) random variables uniformly distributed in [0, 2π], while $n(t)$ represents the AWGN with a double sided power spectral density of $N_0/2$. Note that, since the (U-1) interfering users are in the data transmission process, we assume that their signals are ideally power controlled and the average received power from each interfering signal expressed as P_I. The average received power at the base station from the initial synchronization user power is expressed as P_R.

A widely accepted model for a frequency-selective multipath fading channel is a finite-length tapped delay line with a tap spacing of one chip, for the k^{th} signal, where the L tap weights $\{\alpha_{ki}\}$ are assumed to be i.i.d. Rayleigh random variables with a probability density function (pdf) given by

$$f_{\alpha_{ki}}(x)=\frac{x}{\sigma^2}\exp\left(\frac{x^2}{2\sigma^2}\right), \qquad x\geq 0 \tag{2}$$

where, $E[\alpha_{ki}^2]=2\sigma^2$. In [9], they have derived the statistics for cell-by-cell detection of the matched filter correlator's outputs, Y_I and Y_Q for inphase branch and quadrature branch, respectively, which are approximately Gaussian random processes. Hence, for the conventional detection, the decision variable $Y_1=Y_I^2+Y_Q^2$ represents either an H_1 state or an H_0 state. Given the Gaussian nature of Y_I and Y_Q, and assuming that Y_1 constitutes an H_1 sample, the pdf of Y_1 for the given α_{1l} is the chi-square distribution with two degrees of freedom, which can be expressed as

$$f_{Y1}(y_1\mid H_1)=\frac{1}{2\sigma_0^2}\exp\left(-\frac{m^2+y_1}{2\sigma_0^2}\right)I_0\left(\frac{m\sqrt{y_1}}{\sigma_0^2}\right),\ y_1\geq 0 \tag{3}$$

where,

$$\sigma_0^2=Var[Y_I]=Var[Y_Q]=\frac{(L-1)\alpha^2}{3N}+\frac{(U-1)L\rho\alpha^2}{3N}+\frac{1}{2N\bar{\gamma}_c} \tag{4}$$

$\rho=P_I/P_R$, $\alpha^2=E[\alpha_{kl}^2]=2\sigma^2$ and $\bar{\gamma}_c=P_RT_c/N_0$ represents the signal-to-noise ratio per chip that is SNR/chip. $I_0(\cdot)$ is the modified Bessel function of the first kind with zero order and m is the normalized non-central metric given by [9]

$$m^2=\frac{9}{16}\alpha_{11l}^2 \tag{5}$$

When Y_1 constitutes a H_0 sample, Y_1 is a central chi-square distribution and its pdf can be expressed as

$$f_{Y_1}(y_1\mid H_0)=\frac{1}{2\sigma_0^2}\exp\left(-\frac{y_1}{2\sigma_0^2}\right),\quad y_1\geq 0 \tag{6}$$

Let $Y=Y_1/\sigma_0^2$ be the normalized output of the correlator. It can be shown that Y becomes chi-square distributed with two degrees of freedom; its pdf can be expressed as

$$f_Y(y\mid H_1)=\frac{1}{2}\exp\left(-\frac{S^2+y}{2}\right)I_0\left(S\sqrt{y}\right),\quad y\geq 0 \tag{7}$$

where, $S=\sqrt{m^2/\sigma_0^2}=S_0.(\alpha_{1l}/\alpha)$, with S^2 being the conditional energy-to-noise ratio per path over the N-chip integration dwell-time conditioned on the instantaneous fading parameter α_{1l}, and S_0 is expressed as

$$S_0=\frac{3}{4}\left(\frac{(L-1)}{3N}+\frac{(U-1)L\rho}{3N}+\frac{1}{2N\alpha^2\bar{\gamma}_c}\right)^{-1/2} \tag{8}$$

After absorbing the random variable S, $f_Y(y\mid H_1)$ becomes

$$f_Y(y\mid H_1)=\frac{1}{2(1+\mu)}\exp\left(-\frac{y}{2(1+\mu)}\right),\quad y\geq 0 \tag{9}$$

where, $\mu=9\sigma^2/32\sigma_0^2$. If H_0 is being tested, then

$$f_Y(y\mid H_0)=\frac{1}{2}\exp\left(-\frac{y}{2}\right),\quad y\geq 0 \tag{10}$$

A. CA-CFAR detector

With CA-CFAR processor, the output X_{CA} is the summation of the values in the reference window and is given by

$$X_{CA}=\sum_{i=1}^{M}Z_i \tag{11}$$

The values in the window are summed and scaled by T, where T is set according to the desired false alarm probability. Therefore, the adaptive threshold value of an AD is TX. Since the reference signals in the window cells can be assumed to be noise signals (H_0 cells) [7], the pdf of values Z_j in the windows cells is the same as the H_0 distribution. Also the pdf of H_0 cells can be written as an independent distribution of $G(1,2)$, where $G(\cdot,\cdot)$ is the Gamma distribution. Hence, the pdf of Z_j is

$$f_{Z_j}(z)=G(1,2)=\frac{1}{2}e^{-\frac{z}{2}} \tag{12}$$

$X=X_{CA}=\sum_{j=1}^{M}Z_j$ has the pdf of $G(\sum_{j=1}^{M}1,2)$. The random variable X is written as $G(M,2)$ and its pdf is given by

$$f_X(x)=\frac{1}{\Gamma(M)2^M}x^{M-1}e^{-\frac{x}{2}} \tag{13}$$

where $\Gamma(\cdot)$ is the gamma function.

With CA-CFAR, the probability of false alarm is given by

$$P_{FA}=\int_0^{\infty}f_X(x)\int_{TX}^{\infty}f_{Y|H_o}(y\mid H_0)dydx \tag{14}$$

$$=(1+T)^{-M} \tag{15}$$

The probability of detection is obtained directly from the probability of false alarm of the equation (15), by replacing T by $T/(1+\mu)$.

$$P_D = \left(1+\frac{T}{1+\mu}\right)^{-M} \quad (16)$$

B. OS-CFAR detector

In this case, the input to M reference cells, are stored in an increasing order

$$z_{(1)} \le z_{(2)} \le \cdots \le z_{(k)} \le \cdots z_{(M)} \quad (17)$$

where, $z_{(k)}$ denotes the magnitude of the k^{th} smallest samples. The threshold is obtained by selecting the k^{th} ranked cell to represent the noise and interference level, and then multiplying the input to that cell by a scalar factor T. Let z_k, , $k=1,2,...,M$, be a sequence of statistically *i. i. d.* random variables. The pdf of the k^{th} value of the ordered statistics is given by [10]

$$f_{X_k}(x) = k\binom{M}{k}[1-F_Z(z)]^{M-k}[F_Z(z)]^{k-1} f_Z(z) \quad (18)$$

The probability of false alarm of the OS-CFAR detector is calculated using equations (14), (18) and (10), it is given by

$$P_{FA} = \prod_{i=1}^{k}\left[1+\frac{T}{M-i+1}\right] \quad (19)$$

The probability of detection is determined from equation (19), by replacing T by $T/(1+\mu)$.

C. ANN-CFAR Detector

The artificial neural networks are constructed with neurons that connected to the each other. Each connection has a weight factor and these weights are adjusted in a training process. There are many types of neural networks for various applications in the literature [11]. A commonly used one is the multilayered perceptrons (MLPs).

Multilayered perceptrons (MLPs) are the simplest and therefore most commonly used neural network architectures. MLPs consist of input, hidden and output layers and they have feedforward connections between neurons. Neurons in the input layer only distribute the input signals to neurons in hidden layers by using various activation functions [12].

Weights are changed with various learning algorithm for getting proper output. A typical MLP structure is shown in Fig. 4. The mostly used training algorithm is the back-propagation (BP) algorithm.

The back propagation learning algorithm is composed of forward propagation and back propagation. Forward propagation is the input signal transmitted to output layer via hidden layers. If the output layer gets the desired output, the learning algorithm ends. Otherwise, the back propagation is then realized. The back propagation reversely calculates the errors (the differences between desired outputs and network outputs), then the weights and thresholds of every layer are adjusted by the gradient descent method. Finally, the errors are decreased. The back propagation algorithm is popular in a variety of engineering problems [13].

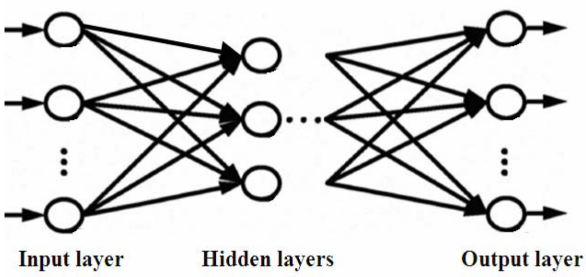

Fig. 4. Structure of the MLP artificial neural network.

✓ *Procedure to Dimension the ANN-CFAR Detector:* The ANN-CFAR detector can be controlled by two parameters, which define the dimension of the MLP. The first one is the number of selected cells or number of MLP inputs (number of reference cells) denoted as M. The second one is the number of hidden layers and its number of neurons, denoted as H_i (i is the number of hidden layers). Both parameters must be optimized at the same time because the optimal solution can give us the butter detector. This procedure is divided in the following steps.

Step 1: Select a desired P_{FA}, and a set of values of M and H_i for this study.

Step 2: Train the MLP with randomly initialized weights. Choose the best trained MLP in terms of the highest P_D for the desired P_{FA}.

Step 3: Repeat the first and the second steps for all the M–H_i pairs.

Step 4: Finally, once we found the best ANN-CFAR detector for each M–H_i pair, we are in conditions of selecting the best M–H_i combination, considering the highest P_D for the desired P_{FA}.

D. Mean Acquisition Time

The mean acquisition time is given by [14]

$$\overline{T}_{acq} \approx \frac{(2-P_D)(1+KP_{FA})}{2P_D}\cdot(q\tau_D) \quad (16)$$

IV. Simulation Results

To study the performance of the proposed adaptive system, the probabilities of detection and false alarm, and mean acquisition time are determined with various parameters. We assume a Rayleigh fading channel, a chip time 10^{-6}sec, a PN sequence of length 1023 and the penalty time $K=1000$.

To produce the ANN-CFAR detector, we generated a training base of 1320 samples having an exponential distribution in homogeneous and nonhomogeneous environment, for several values of SNR/chip, several values of interfering cells with various powers. After several tests, we observed that the best number of input is M+1, with M=32. The number of neurons of hidden layers is 17 for one hidden layer network, 19 and 8 respectively, for two hidden layers network. The output layer contains only one neuron, because we need a decision about the presence (or the absence) of the desired signal. The simulation base of the false alarm probability contains 10^4 samples.

The first part of results shows the influence of the following parameters on the convergence of our network: the number of hidden neurons, the training rate and the number of iterations. According to simulation results, shown by figures 5, 6 and 7, we demonstrate that increasing the number of hidden neurons, the training rate and the number of iteration can minimize the mean square error (MSE) and make the convergence of the network faster. For butter performance, the value of the MSE should not be lower than 10^{-2} to avoid the overfitting problem. In figure 8, we demonstrate how we can fix the false alarm rate using the threshold of the output neuron.

In tab.1, we give threshold values of CA, OS and ANN-CFAR detectors for different values of desired probability of false alarm. We can see in table 2 that, we can regulate the probability of false alarm using ANN-CFAR algorithm in good manner comparing to CA and OS-CFAR algorithms.

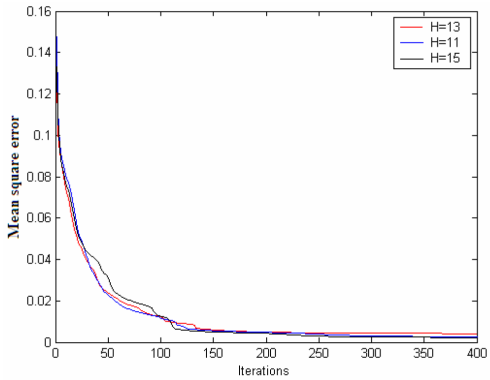

Fig. 5. Mean square error versus the number of iterations for $\mu = 0.2$, and different numbers of hidden neurons.

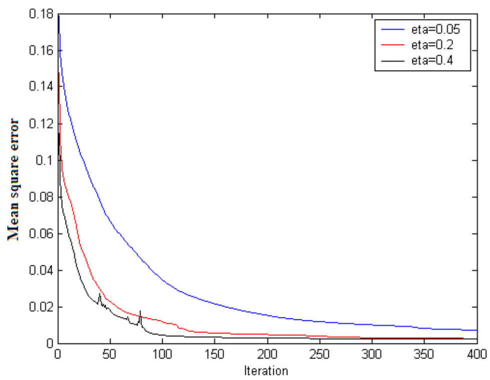

Fig. 6. Mean square error versus the number of iterations for 11 hidden neurons, and different values of training rate.

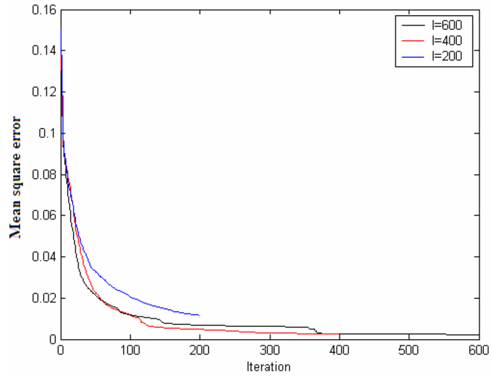

Fig. 7. Mean square error versus the number of iterations for 11 hidden neurons and $\mu = 0.2$.

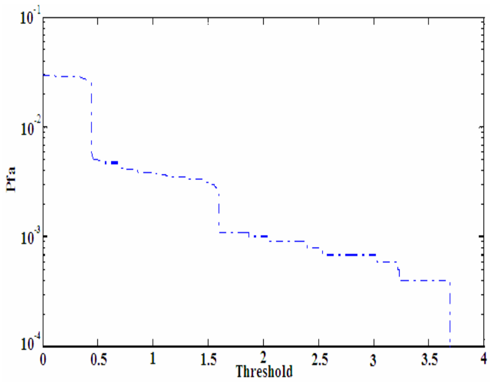

Fig. 8. Probability of false alarm versus the threshold of the output neuron.

Tab.1. Thresholds of different CFAR algorithms for different values of P_{FA}.

	ANN-CFAR	CA-CFAR	OS-CFAR
P_{FA}=0.1	0.112	0.0746	1.8156
P_{FA}=0.01	3.62985	0.1548	3.8383
P_{FA}=0.001	3.6405	0.2409	6.0863

Tab.2. The variation of P_{FA} around the desired values for different CFAR algorithm.

		ANN-CFAR	CA-CFAR	OS-CFAR
P_{FA}=0.1	Min (P_{FA})	0.0907	0.0892	0.0892
	Max (P_{FA})	0.1099	0.1117	0.1111
P_{FA}=0.01	Min (P_{FA})	0.0072	0.0074	0.0068
	Max (P_{FA})	0.0132	0.0134	0.0128
P_{FA}=0.001	Min (P_{FA})	0.0008	0.0002	0.0003
	Max (P_{FA})	0.004	0.0022	0.002

It is clear that the interval of the probability of false alarm variation of ANN-CFAR detectors is small comparing to the other algorithms in almost of cases.

In figure 9, we need to demonstrate that we can approximately regulate the probability of false alarm around a desired value, for different situations, using ANN-CFAR algorithm.

We show in figures 10 and 11, the performance of the proposed ANN-CFAR detector.

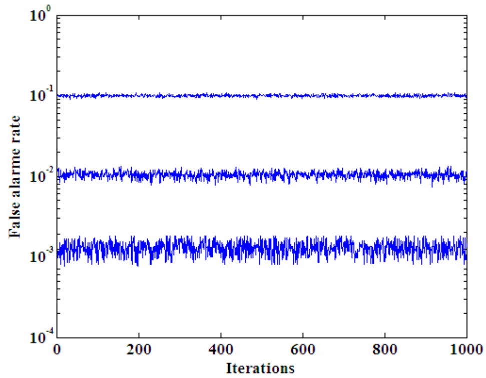

Fig.9. Simulation of the probability of false alarm versus the number of iterations.

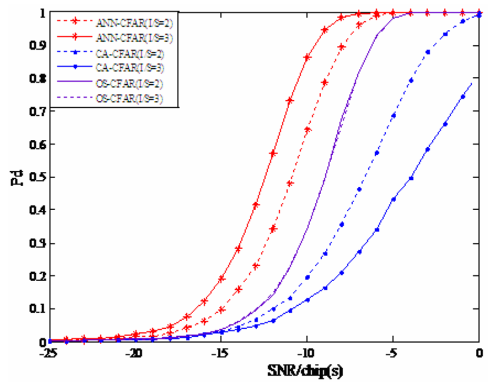

Fig.10. Probability of detection versus SNR/Chip for $M=32$, $P_{FA}=10^{-3}$, different power in the tow interfering cells, using two hidden layers network.

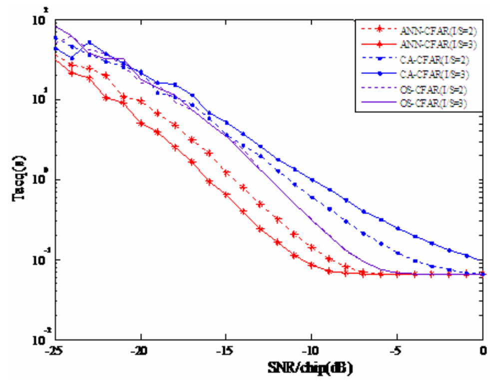

Fig.11. Mean acquisition time versus SNR/Chip for $M=32$, $P_{FA}=10^{-3}$, different power in the tow interfering cells, using two hidden layers network.

It is clear that the probability of detection of this detector outperform CA and OS-CFAR detectors, in nonhomogenous situation that is characterized by the presence of random power interferences. The same remarks can given for the mean acquisition time.

V. CONCLUSION

In this paper, we analyzed the backpropagation artificial neural network performance, for the detection of DS/CDMA signals in nonhomogenous Rayleigh fading channels. We compare the performance of the ANN-CFAR detector with the CA-CFAR and OS-CFAR detectors. The results showed that the artificial neural network is a good solution to solve the problem of detection in the presence of multiple access interferences. Using this algorithm, we can regulate the probability of false alarm; we can ameliorate the probability of detection and the mean acquisition time.

REFERENCES

[1] K.Sangchoon, "Acquisition Performance of CDMA System With Multiple Antennas,"IEEE Trans. on Vehicular Technology, vol. 53, No. 5, pp. 1341–1353, September 2004.

[2] Y. Lie-Liang and H. Lajos, "Serial Acquisition of DS-CDMA Signals in Multipath Fading Mobile Channels," IEEE Trans. on Vehicular Technology, vol. 50, No. 2, pp. 617–628, March 2001.

[3] S. Kim,"Effect of Spatial Fading Correlation on CDMA Code-Acquisition Performance," IEE Proc.-Commun., Vol. 152, No. 1, pp. 103–112, February 2005.

[4] E. A. Sourour and S. C. Gupta, " Direct-Sequence Spread-Spectrum Parallel Acquisition in a Fading Mobile Channel", IEEE Transactions on Communications, Volume 38, No. 7, pp 992-998, July 1990.

[5] J. H. L. Linatti, "On the Threshold Setting Principles in Code Acquisition of DS-SS Signals," IEEE. Journal on Selected Areas in Communications, Volume 18, No. 1, January 2000.

[6] L. Hacini, A. Farrouki and Z. Hammoudi, "Adaptive Hybrid Acquisition of PN Sequences Based on Automatic Multipath Cancellationin Frequency-Selective Rayleigh Fading Channels," Wireless Pers. Commun., vol.63, pp.147–166, 2012.

[7] H.-S. Oh and D.-S. Han, "An Adaptive Doubel-Dwell PN Code Acquisition System in DS-CDMA Communications", Elsevier, Signal Processing, vol. 85, pp. 2327-2337, May 2005.

[8] P. P. Gandhi and S. A. Kassam, "Analysis of CFAR Processors in Nonhomogeneous Background," IEEE Trans. on Aerospace and Electronic Systems, vol. 24, No. 4, pp. 427-445, July 1988.

[9] Yang L. L. and Hanzo, L." Serial Acquisition of DS-CDMA Signals in multipath Fading Mobile Channels", *IEEE Transactions on Vehicular Technology*, Volume 50, No.2, pp. 617-625, March 2001.

[10] H. Rohling, "Radar CFAR thresholding in clutter and multiple target situations," IEEE Transactions on Aerospace and Electronic Systems, vol.19, No.4, pp. 608-621, July 1983.

[11] U. Mitra and H.V. Poor, "Neural network techniques for adaptive multiuser demodulation," IEEE Journal of Selected Areas in Comm, vol. 12, No.9, pp.1460–1470, 1994.

[12] M. T. Hagan, H. B. Demuth and , M. Beale: Neural network design, PWS Publishing Company, 1996.

[13] L. Fausett: Fundamentals of Neural Networks, Prentice-Hall, 1994.

[14] A. Aissaoui, Z. Hammoudi and A. Farrouki, "Adaptive pseudo-noise code acquisition scheme using automatic censoring for DS/SS communication in frequency-selective Rayleigh fading channel," IET Commun., vol.2, No.2, pp. 359–365, 2008.