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REVIEW PAPER

Soft Computing for Robust Secure Wireless Reception

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ABSTRACT

Soft computing is a collection of different computing methodologies that include neuro computing, fuzzy logic, evolutionary computing, and probabilistic reasoning. These are aimed to exploit the tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost. This paper presents a brief overview of soft computing components, followed by typical realization, via simulation of a wireless receiver employing a hybrid soft computing technique to illustrate its application in a fading signal propagation scenario.

Keywords: Soft computing, neural networks, fuzzy logic, genetic algorithm, robust secure wireless reception, higher-order statistics

1. INTRODUCTION

Soft computing (SC) is a term originally coined by Zadeh [1] to denote systems that exploit the tolerance for imprecision, uncertainty, and partial truth to achieve tractability, robustness, low solution cost, and better rapport with reality. Traditionally, SC has been constituted by four technical disciplines. The first two, probabilistic reasoning (PR) and fuzzy logic (FL) reasoning systems, are based on knowledge-driven reasoning. The other two technical disciplines, neuro computing (NC) and evolutionary computing (EC), are data-driven search and optimisation approaches [2].

The core of modern computers is digital, and at the very low level (Boolean logic), only 0 or 1 exist (TRUE or FALSE, ON or OFF). The properties in the real world, on the other hand, are often different from this black-and-white thinking, which often is the reason for problems in real-life physical systems, where a system views its components either as correct (according to its pre-specified basis or range) or incorrect (outside the basis or range). So, a component of the system that provides its output only a little bit offside its specification might be judged or inferred as correct or incorrect by a correct system, which causes a divergence in the correct system states. To overcome such real-life complexities such as imprecision, the computer paradigm of soft computing is used. Soft computing is a general term for a coalition of methodologies such as fuzzy logic, neuro- computing, evolutionary computing, probabilistic computing, chaotic computing, and machine learning [1,3].

Many soft computing approaches are also sometimes referred to as biologically inspired ones and hence there is a great deal of similarity among them. Most biological systems have to work autonomously. Usually, there is no one to help a creature in recovering from a breakdown. Of course, there is positive interaction between individuals. Also, biological systems are always optimised to the goals such as creation effort, maintenance effort, size, weight, power consumption, etc.

Some of the biologically-inspired approaches fall into the category of intelligent systems, neural network being a typical example. Naturally, the word intelligent (as well as the words smart, wise, clever) transport a very positive meaning. Intelligence refers to the overall effectiveness of an individual's mental processes, particularly his or her comprehension, learning, memory, recall, abstraction, association, and reasoning capabilities. When intelligence is generally seen as the capability to solve (new) problems, it is possible to identify intelligent solutions in engineering. This refers to the systems that are able to react appropriately to changing situations (adaptively) without input from a human operator. This definition, of course, encompasses a wide range of engineering applications and many different methods and algorithms. The research on intelligent systems is motivated by the high versatility of such systems, which makes it possible to reuse many algorithm successfully in different applications.

Naturally, an intelligent system might not be the best universal solution for a given application. For example, a racing car is specifically designed for good roads, while the human legs can adapt well to various terrains like grassland, water, mountains, etc. Therefore, the human locomotor system represents an intelligent system while the former is not. An intelligent system need not be complex also. Even primitive biological systems tend to solve these types of tasks (so called complex problems for the present day computers) in a simple and effective way.

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2. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks are networks or systems formed out of many, highly interconnected nonlinear memoryless computing elements [4]. The pattern of interconnection can be represented mathematically as an array of weights in which the nodes represent basic computing elements, as shown in Fig. 1.

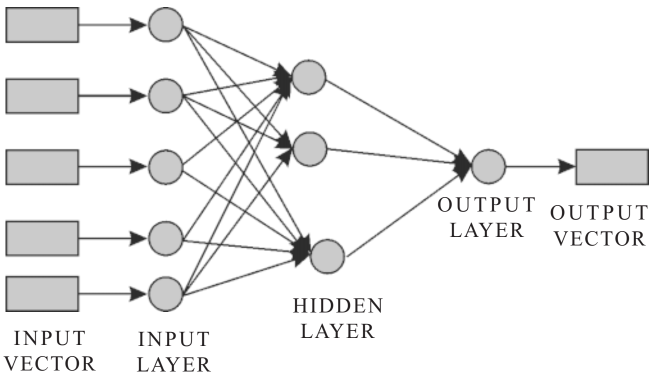

Figure 1. Simple three-layered network.

The links or edges represent the connections between the elements, the weights represent the strength of the interconnections, and the directions establish the flow of information and define inputs and outputs of nodes of the network. The feed-forward artificial neural network (FANN), or otherwise known as multi-layered perceptron, is an effective methodology for the construction of truly nonlinear systems accepting large number of inputs and achieving success in applications to signal processing, pattern classification, and forecasting. For successful results, the network is trained with different data samples [5].

The knowledge stored in the artificial neural network is represented by the weights associated with each link. The learning process of artificial neural network is termed the training of the network. Backpropagation is the most popular technique used for training the artificial neural network.

The impressive learning feature of an ANN enables such systems to adapt to changing conditions. ANN supports supervised and unsupervised learning. In supervised learning, backpropagation ANNs are used. During a training phase, the parameters of the ANN are adapted until the system performs the desired function. The trained system is then able to perform the programmed function with a high robustness against errors. Unsupervised learning algorithm try to extract common sets of features from the input data. A typical example for an unsupervised learning artificial ANN is Kohonen's self-organizing map (SOM). Unsupervised learning algorithms are used for automatic classification, modelling, and data compression systems [6].

The ANN architecture is often problem-specific and there are no hard and fast guidelines except for the trial and error mechanism. However, the complex the artificial neural network, the longer is the training time required, and the lesser the probability of error convergence. Artificial neural networks are not 100 per cent correct, but it is better to converge to a solution which is 99 per cent correct in a few ms, rather than have a 100 per cent correct solution in many hours. Drawbacks of ANNs are its black-box data processing structure, and in some cases, a slow convergence speed. Thus, the data processing mechanism of an ANN cannot be programmed, understood, or verified in terms of rules.

Typical problems addressed by neural networks include pattern recognition, signal processing, time series processing, unsupervised clustering, and visualisation of complex data, data compression, control problems and image processing. A wide range of current applications of pattern recognition include security applications, fingerprint recognition, signature verification, secure entry systems, and intelligent alarms.

Some other examples of existing neural network pattern-recognition high-level applications in telecommunications are data interpretation equalisers, network design, management, routing and control, ATM network control, fault management, network monitoring, signal processing for beamforming, adaptive antennas, consumer communications and radio resource management and mobility management [7].

3. GENETIC ALGORITHM

Genetic algorithm (GA) form a family of computational models inspired by evolution. The concept of a GA is based on optimisation of the search strategies relying on the Darwinian principle of natural selection and evolution (survival of the fittest).These are derivative free stochastic optimisation methods [6]. These algorithms encode a potential solution to a specific problem on a simple chromosome-like data structure and apply recombination operators to these structures so as to preserve critical information. Genetic algorithm are often viewed as function optimisers, although the range of problems to which genetic algorithm have been applied is quite broad.

An implementation of a genetic algorithm begins with a typically random population of chromosomes (genes). In addition, a GA needs an algorithm that allows to cross-mix these genes, and a fitness function that produces a comparable value on the quality of an actual solution. One then evaluates these structures and allocates reproductive functions (recombination and mutation) in such a way that those chromosomes, which represent a better solution to the target problem, are given more chances to reproduce (survival) than those chromosomes which offer poorer solutions. After recombination and mutation of genes, the GA uses the fitness function to select the best genes, for the new population. By making multiple iterations, the GA approaches a solution that is equal to or better than the start value. The goodness of a solution is typically defined wrt to the current population. Figure 2 shows a typical flow chart of a genetic algorithm.

The genetic algorithm is some kind of search algorithm that is advantageous if the given search space is too large to be searched by exhaustive search algorithm and too unstructured to be able to use straight-forward search algorithm. Moreover, a GA needs only a minimum of information about the problem to be solved, and thus, can be easily applied. GAs are usually very fast in finding a good solution, but in general, these will not be able to find the best solution.

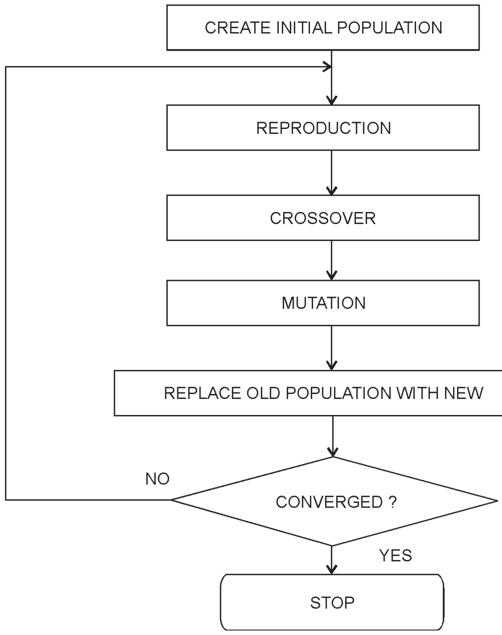

Figure 2. Typical flow chart of a genetic algorithm.

Many genetic algorithm models are application-oriented and hence used as optimization tools.

4. FUZZY SYSTEMS

A classical set or crisp set in mathematics is a set with a boundary. Crisp applications are adequate for various applications and an important tool in mathematics and science. However they do not conform to human nature and thoughts, which are abstract and imprecise. In contrast to crisp set, a fuzzy set is without a crisp boundary. This signifies the transition from belong to set and not belong to set is gradual [6].

In a narrow sense, fuzzy logic refers to a logical system that generalises the classical two-value logic for reasoning under uncertainty. In broader terms, fuzzy logic refers to a collection of theories and technologies that employ fuzzy sets, which are classes of objects without sharp boundaries. In contrast, fuzzy logic generalises the crisp TRUE-and-FALSE (black and white) concept fundamental to classical logic, to a matter of degree covering a range of values. In other words, fuzzy logic forms a bridge between digital rules (for example, if height is greater than 6 ft, then he is tall) and imprecise information (for example, height is between 5 ft and 6 ft). This smooth transition is characterised by membership functions that give flexibility in modelling linguistic expressions. The membership function of an object specifies the degree of similarity with the fuzzy set.

Fuzzy inference is the process of mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made or patterns discerned. The process of fuzzy inference involves all the concepts such as membership functions, if then rules, and fuzzy operators. The essential components of a fuzzy system are the fuzzifier, fuzzy inference engine, fuzzy rule base, and defuzzifier (Fig. 3).

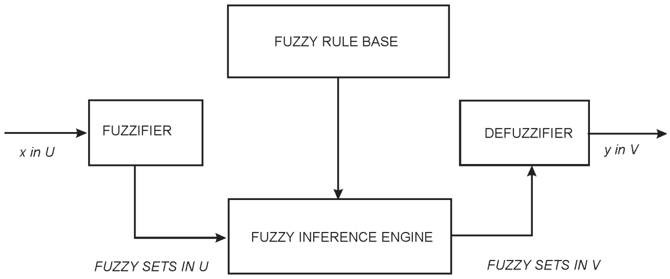

Figure 3. General model of a fuzzy system.

The inference method of fuzzy logic is similar to the human brain. Fuzzy logic supports the implementation of algorithms for imprecise input parameter values that perform better than traditional methods. The distinct advantages brought forth by fuzzy logic are the ease of describing human knowledge involving vague concepts, and the enhanced ability to develop cost-effective solutions to practical problems. However, fuzzy logic has the drawback of lacking an effective learning mechanism; auto tuning a classical fuzzy system is difficult.

5. HYBRID SYSTEMS

Each of the above discussed methods provides efficient solutions to a wide range of problems belonging to different domains. Attempts are being made to synergize and integrate judiciously the three different technologies, in whole or in part, to solve problems for which each one of these alone can not give any solution. This is intended to minimise their individual weaknesses, and at the same time, take advantage of their strengths in applications. However, hybridisation should only be performed when better solutions are guaranted [6].

As an example, the combination of fuzzy systems with neural networks overcomes some problems of ANNs and fuzzy logic, by providing an adaptive system with a rule-based model. Such neuro-fuzzy systems employ learning algorithm of an ANN to determine the parameters of a fuzzy inference system. Unlike ANNs, a neuro-fuzzy system is always interpretable in terms of fuzzy if-then rules, thus giving insight into the model.

6. WIRELESS COMMUNICATION

The field of wireless communication has been experiencing an explosive growth in terms of technology, number of subscribers, coverage and the type of services in the last 20 years, and the trend is expected to continue for long. New systems and standards are coming up which enable broadband wireless communication in the office, at home, and while on the move.

With this tremendous growth, it also faces problems of different types for which no single simple solution seems possible. The available frequency spectrum is all the more congested, making it polluted with full of interference. This makes the secure reception of any particular signal a tedious task [8, 9].

Spread spectrum is an RF communication system in which the baseband signal bandwidth is intentionally spread over a larger bandwidth by injecting a higher frequency signal. As a direct consequence, energy used in transmitting the signal is spread over a wider bandwidth, and appears as noise. Its advantages are manifold [10, 11]; providing resistance to jamming and interference, reducing the probability of intercept by adversaries, and providing resistance to interference from multi-path as well as multi-user signals.

Originally, the spread spectrum technology was developed for military use, but its modern applications utilise its resistance to interference properties to provide multi-path rejection in ground - based mobile radio environments, and multiple access communications, in which a number of independent users can share a common channel without requiring for an external synchronization mechanism (multi-user communication).

The multi-user communication over multi-paths poses many problems such as multiple access interference (MAI), co-channel interference (CCI) and near-far effect, which ultimately degrade the system performance of signal to noise ratio (SNR) and bit-error rate (BER) performance [12]. The capabilities of conventional techniques of reception are limited in this respect and new computationally complex techniques are being tried by researchers.

Recently with the advent of computers, soft techniques have gained much popularity as these can provide improved performance over the conventional ones. Also, these possess the advantages of high flexibility, adaptability, and low implementation costs.

6.1 Implementation of a Robust Secure Wireless Reception

This section describes the simulation work in devising a hybrid soft computing scheme for the blind multi - user reception problem. Specifically, this work implemented the blind source recovery of CDMA channels using genetic algorithm assisted neural network in a rayleigh fading channel scenario. Figure 4 shows the block level representation of the whole transmit-receive (base band only) chain where the * marked blocks form the proposed soft computing scheme of blind receiver.

In blind reception, the channel or signal is estimated based on prior knowledge of temporal or spatial signal or channel properties, either statistically or deterministically, without access to either the actual input or the channel values [13]. In the present implementation, only the spreading codes of the user(s) of interest have been used for the detection. A two-step adaptive reception method was followed.

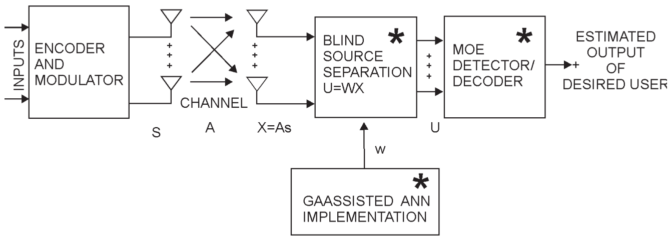

Figure 4. Proposed receiver scheme.

The first step separated (blind source separation) the user signals without explicit channel estimation. The GA-assisted-NN block computes the source separation matrix for this step. Here, a higher order statistical (HOS) approach known as independent component analysis (ICA) was used for the blind separation of the user signals [14]. The ANN was initially trained (weights adjusted) with known signals. The weights were arrived at and optimised using GA, the fitness function being the convergence condition. This was followed by the adaptive detection based on the principle of minimum output energy (MOE) [15].

6.2 Independent Component Analysis

Independent component analysis (ICA) is a statistical computational model [16,17] that uses linear transformations on multidimensional data to interpret the spectral signatures of the mixed signal. Given a set of observations of random variables ($x_1(t)$,$x_2(t)$,….. $x_n(t)$), where t is the time or sample index, assume that these are generated as a linear mixture of independent components s (Fig. 4),

$$X=As \tag{1}$$

where A is some unknown matrix, and X, the observation vector. Signal recovery now consists of estimating both the matrix A and the $s_i(t)$, when only the $x_i(t)$ is observable.

Alternatively, ICA is defined as follows:

Find a linear transformation given by a matrix W so that the random variables $y_i(t)$, $i=1,....n$ are as independent as possible. In other words,

$$U = WX = WAs \tag{2}$$

which indicates that estimation of A gives W by taking its inverse. The model in Eqn (1) can be estimated if and only if the components are non-Gaussian [16]. Here U is the output vector, an estimate of the possibly scaled and permutated source vector. This corresponds to U expressed in the form

$$U = WX = WAs \rightarrow DPs \tag{3}$$

where D is a non-singular diagonal matrix and P is a permutation matrix. At most, one source is allowed to be Gaussian, to ensure the identifiability. The theoretical solutions of the blind-separation problem are commonly based on maximum-likelihood estimation, minimisation of mutual information, or infomax [4].

6.3 Minimum Output Energy Detector

The detection of the desired user was done through an adaptive MUD algorithm [15]. The characterising equations are, for minimum output energy,

$$MOE(x)=E\{(<y,s+x>)^2\} \tag{4}$$

and for the adaptation,

$$x[i]=x[i-1]-\mu Z[i](y[i]-Z_{mf}[i]s) \tag{5}$$

where, Z_{mf} is the matched filter estimate of the symbol concerned and μ the step size for adaptive updation. Here, no training sequence is required to implement the gradient descent algorithm.

For a comparison, the following conventional detectors were considered. For the received signal y the bit estimate is,

For matched filter (MF),

$$\hat{b} = \mathrm{sgn}(y) \tag{6}$$

For cor-relator: $\hat{b} = \mathrm{sgn}(R^{-1}y)$ (7)

where, R is the correlation matrix.

And for MMSE detector

$$\hat{b} = \mathrm{sgn}((R + N_0 A^{-2})^{-1} y) \tag{8}$$

where, A is the amplitude matrix and N_0 the noise power.

The envelope of a complex Gaussian distributed variable is Rayleigh distributed [8], which has a pdf:

$$\begin{aligned} p(r) &= \frac{r}{\sigma^2}\exp\left(-\frac{r^2}{2\sigma^2}\right) \quad \textit{for } r > 0 \\ &= 0 \quad \textit{otherwise} \end{aligned} \tag{9}$$

where, r is the envelope of the received signal, and $[2\sigma^2]$ is the pre-detection mean power.

For a comparison of the error probability, the theoretical AWGN [9,18] has

$$P_e = \frac{1}{2} erfc\left(\sqrt{\frac{E_b}{N_o}}\right) \tag{10}$$

and for the theoretical limit of Rayleigh fading,

$$\begin{aligned} P_e &= \frac{1}{2}\left[1-\sqrt{\frac{\Gamma}{1+\Gamma}}\right] \quad \textit{for } \Gamma < 10\,dB \\ &= \frac{1}{4\Gamma} \quad \textit{for } \Gamma \geq 10\,dB \end{aligned} \tag{11}$$

where, Γ is the Rayleigh faded average E_b/N_o [19].

6.4 Simulation Setup

For the simulation, the channel considered was Gaussian (AWGN) with a flat Rayleigh fading condition, which is usually the real case. No power control was assumed for the transmitter signals. The signal model taken was for the baseband case without any source or channel coding.

The simulations were designed to examine the proposed multi-user CDMA system with active users K= 3. Figure 5 shows the signal flow path for one such user. Only the baseband model was considered for the simulation. Gold sequences of length 31 are used for the spreading. Only the synchronous case was considered for the simulations.

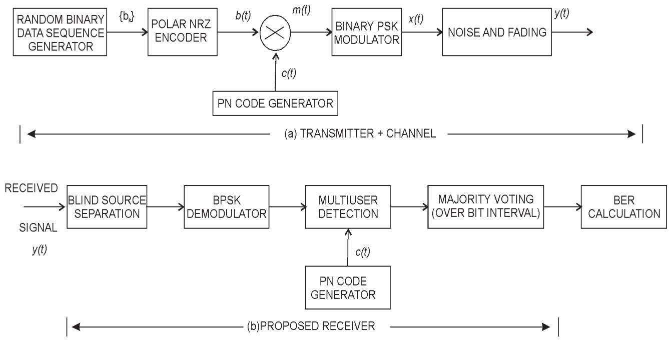

Figure 5. Setup for the k^{th} user.

Performance of the multi-user detector was measured in terms of the bit-error rate (BER) for varying SNRs. The empirical BER for a user of interest can be computed as the ratio of the number of incorrectly estimated bits to the total number of received bits as.

$$BER = \frac{\textit{Number of wrongly estimated bits}}{\textit{Total number of bits received}} \tag{12}$$

The simulations used the Monte Carlo (MC) technique [20]. Throughout the experiments, the number of simulation runs, which stands here for the transmitted bits, were set at N = 10000 (minimum). Similar runs are iterated (here 5 to 10 times) and the results averaged to get the performance parameter value under evaluation. It is assumed that signature codes of all users are known in advance at the receiver. The simulation tool used is Matlab.

6.5 Signal Model

The system model for a synchronous digital DS-SS CDMA with coherent Binary Phase Shift Keying modulation format can be described by a received signal [12].

$$r(t) = \sum_{i=0}^{M-1}\sum_{k=1}^{K} A_k b_k(i) s_k(t - i\tau_b) + n(t) \tag{13}$$

where K is the number of active users, M is the length of data transmitted by each user, A_k is the amplitude of the component of the received signal from the k^{th} user, $b_k(i)$ denotes the i^{th} bit of the k^{th} user's message, and $s_k(t)$ is the signature waveform for the k^{th} user. This is defined for $0 \leq t < \tau_b$. Here, $n(t)$ is the channel noise added to the DS-SS signal in transmission and τ_b is the bit period common to all the synchronous users. This general equation may be simplified to represent only the i^{th} bit of data transmitted as follows:

$$r(i) = \sum_{k=1}^{K} A_k b_k(i) s_k + n(i) \tag{14}$$

where $n(i)$ is a length N vector of noise samples generated for the i^{th} bit transmitted. This equation for the i^{th} received bit may then be represented in matrix form (indicated by bold letters):

$$r(i)=SAb(i)+n(i) \tag{15}$$

where $r(i)$ is a length N vector of representing the i^{th} bit transmitted, R is the $K \times N$ code matrix, comprised the length N signature sequences for each of the K users, A is a $K \times K$ diagonal matrix of user amplitudes such that $A = \text{diag}(A_1, \ldots, A_K)$, $b(i)$ is the length K vector of the i^{th} bits transmitted by each user, $n(i)$ is a length N vector of noise samples generated for the i^{th} bit transmitted.

7. RESULTS AND DISCUSSION

Figures 6 and 7 show the results of the simulation in both the AWGN and Rayleigh fading channel conditions. Figure 6 gives the performance of the conventional detectors. It can be seen that these detectors perform poorly in fading condition. Figure 7 gives the performance of the proposed scheme. For comparison, the theoretical limits of AWGN (for BPSK) and Rayleigh fading were taken. Here, the conventional MF (Rayleigh) performance was outside the limits. The proposed scheme performed exceptionally well, even in the fading condition.

This scheme also outperforms many of the detection schemes reported in the published literature [16,21]. In the former [16], a nonlinear denoising source separation is employed for the reception without considering any multi-path propagation. The later [21] uses a parallel factorisation method (PARAFAC) for the blind detection.

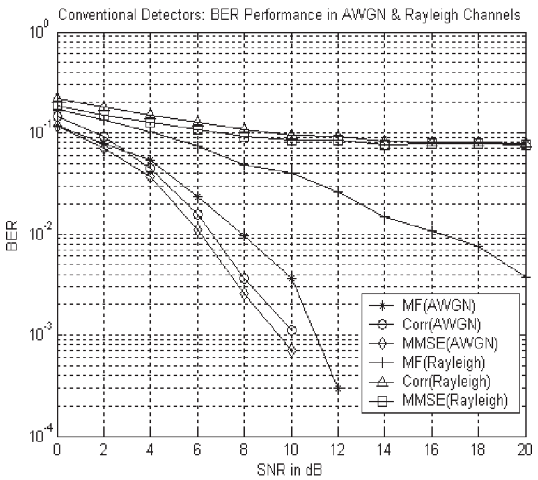

Figure 6. BER Versus SNR curve of conventional detectors.

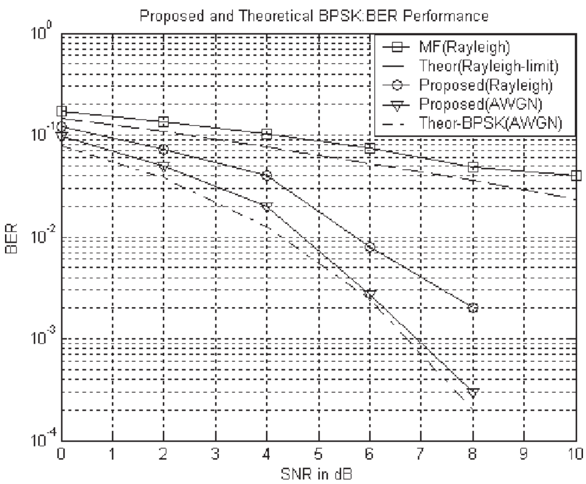

Figure 7. BER Versus SNR curve of proposed scheme.

The proposed scheme exploits the characteristic properties [2,3] of both the ANN and GA in making a definite solution (decision) from the imprecise and uncertain nature of the received signal point in the signal space. The adaptive nature of the scheme [16] provides enough tracking power (tractability for the signal immersed in noise) which in turn makes it robust in noisy fading channel conditions. This scheme is also secure to the extent of the use of a secret user-specific code which will be known only to the authorised transmitter and receiver. The soft computing part can replace a definite portion of system hardware, reducing the cost, at the same time, improving the flexibility (system programmability).

8. CONCLUSION

In this paper, a brief review of the popular soft computing techniques has been presented. As an illustration, a hybrid neuro-genetic method was devised for solving the problem of blind reception of CDMA signals in fading channels. The included simulations show a drastic improvement of the hybrid neuro-genetic scheme over the conventional ones in AWGN noise and fading channels. This implies a degree of robustness in addition to the secure nature.

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