Volume 6, Issue 1, January 2019 ISSN: 2348-8565 (Online)

International Journal of Modern Engineering and Research Technology

Website: http://www.ijmert.org Email: editor.ijmert@gmail.com

Genetic Algorithm: An Adaptive Approach to Improve BER in Turbo Codes

Suman Kshirsagar
Assistant Professor
Department of Electronics and Communication Engg,
Chaitanya Bharathi Institute of Technology
Hyderabad, (T.S.) [INDIA]
Email: suman_me192@cbit.ac.in

ABSTRACT

This paper tells the importance of Genetic Algorithm in error correcting codes from different point of view. As a matter of discussion, Turbo codes, 3D Turbo codes and A3D Turbo codes have been selected. 3D-TC is the development over Turbo Codes and A3D -TC are improvement over 3D-TC, where the control parameters, permeability and permittivity are made adaptive by using Genetic Algorithm based knowledge source and feeding it to feed forward neural network. Extensive experimental results prove the performance of A3D-TC over the conventional 3D-TC under various noisy environments and can be used to control errors in mobile communication.

Keywords—*Turbo codes, 3D-TC, A3D-TC, Neural Network, knowledge source, parameters, adaptive, permeability, permittivity, Genetic algorithm.*

I. INTRODUCTION

Introduction of error control codes in various communication systems improves the efficiency and accuracy of the transmitted information. Hence the coding used for controlling errors has always been a crucial part in the design of modern communication and digital storage systems.

II. How Does An Error Occur

The error may occur in many ways depending on the message signal transmitted through the channel.

For example
If the message is in the form of bits

Transmitted data bits 10001101100100111010

Received data bits 10100110100100011010

The underlined bits indicate that they are in error.

Figure 1 below shows how the signal is transmitted from the transmitter to the antenna and then received at the receiver. The signal received is a corrupted signal.

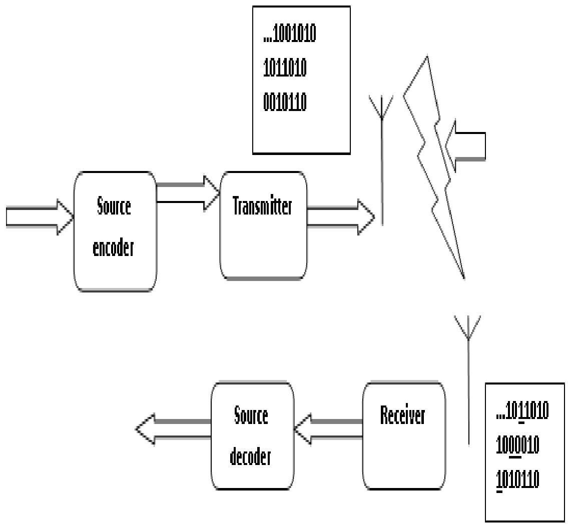

Figure: 1. Model of Text message

If the signal is in error, then the communication system is unreliable.

III. Error Correction Codes

There is a need for error correcting codes. The information sequence that is to be transmitted consists of several parts with different degrees of significance. Hence, there is a need for different levels of protection against noise [8]. As the information is transmitted over the communication channel, noise in the channel results in errors in the sequence. The information therefore has to be protected from occurrence of errors. Protection is done by a method called coding or channel coding, where information is disguised using different codes.

A set of symbols are attached with meanings or values which are called as codes [3]. These codes are designed to provide data protection at different levels.

The elemental concept of error control coding is the addition of redundancy which converts the transmitted bits to a longer sequence of bits (codeword) to combat errors introduced by the noise in the channels. The redundancy is added at the transmitter and the exploitation of this redundancy is done at the receiver to detect and / or correct errors.

Types of Codes

Codes are classified as Backward Error Correction codes and Forward Error Correction codes.

Forward Error Correction (FEC) shown in figure 2, is often used for error protection and to improve the reliability of transmission [10]. The use of FEC codes in communication system is an integral part of ensuring reliable communication and these codes have become inevitable in wireless based digital communication systems as they allow the system to operate at lower SNR ratio [1].

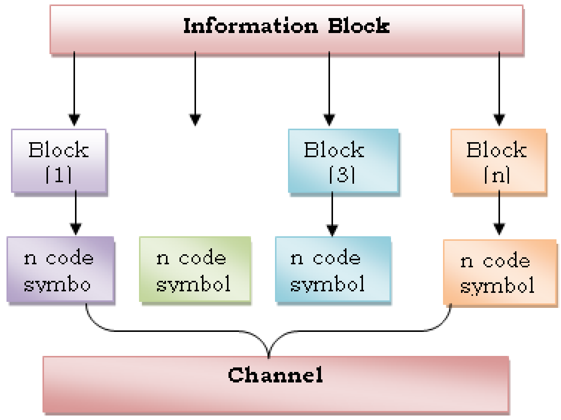

Figure: 2 Forward Error Correction

The use of Forward Error Correction codes has become inevitable in wireless digital communication systems as they allow the system to operate at low signal to noise (SNR) ratio.

There are basically two types of FEC codes:

1. Linear Block codes
2. Convolution codes

We are concentrating more on Convolution codes.

The wide acceptance of convolution codes resulted into many advances which helped to extend and improve this basic coding scheme. This advancement resulted in Turbo Codes.

Turbo Codes

Turbo codes are considered to be the most powerful FEC code. They formed the foundation for many research works looking into the design, analysis and use of iterative decoding in digital communications [11]. They are gaining importance in designing of current communication system as they provide close to optimal bit error rates at lesser signal to noise ratios for data transmission. They increase the available bandwidth without increasing the transmission of power or they can be used to decrease the amount of power required for transmission at a particular data rate. [12]. The development of turbo codes gave rise to a new interest in identifying the proximity of practical codes to the Shannon limit on code performance [2]. They are the only codes with the performance in the threshold limits of reliable communication as stipulated by Shannon [5]. The performance of these codes over low SNR domains is remarkable [6].

In contradiction to the conditions in AWGN channel, turbo code based on RSC codes and turbo codes with differing interleaver sizes show similar working for changed constraint lengths and generator polynomials. In quasi-static fading channel with antenna diversity, turbo codes cannot do better than convolutional codes. But in the same channel with antenna diversity they can outperform convolutional codes.

In [13] this paper the description was about the stopping set of turbo codes used in binary erasure channel. Iterative decoding technique was used. Using this they could study about the block and bit erasure probabilities. It was found that both the probabilities are better than those with maximum likelihood decoding (ML), and have insignificant error floor differences. The stopping set and the low weight code words dominate the error floor working of turbo codes with iterative decoding. A research activity was performed on the study of turbo codes with iterative decoding in all directions. BER performance of these codes was evaluated and predicted in AWGN channel. Maximum likelihood decoding is preferred over iterative decoding.

A modified 3D turbo code was [14] presented. To make certain huge asymptotic gains at extremely small error rates, the minimum Hamming distance (d_{min}) of a turbo code will not be sufficient. The minimum Hamming distance was improved by using component encoders with more number of states constructed with advanced internal permutations or by raising the number of component encoders. They proposed a rate-1 third encoder where bits are encoded. They combined the characteristics of both parallel and serial concatenation so that conventional turbo codes can have increase d_{min}. This led to new code called 3D-TC. This code's versatility is well accepted in terms of coding rate and block size. These codes enable large degrees of parallelism based on simplicity of models, which make internal permutations simple.

The proposed 3D-TC improved 3GPP2 code in the error floor significantly. It showed slightly better convergence than serial concatenated convolutional codes (SCCC). It also resulted in improvement of performance in the flattening region in relation to 8-state conventional turbo code but all at the cost of increase in complexity. 3D EXIT chart analysis was proposed in [15]. Extrinsic Information Transfer (EXIT) chart facilitates to understand the convergence behavior of iterative decoders. When systematic bits are punctured at regular intervals to measure the behavior of turbo codes, the conventional EXIT chart analysis was not successful.

They proposed a new 3D EXIT chart technique in which the performance of turbo codes was perfectly modeled. A periodic pattern was followed and punctured at regular intervals. They concluded that "the code designed with the help of the 3D EXIT chart tool was outperforming the arbitrarily punctured scheme".

From the above review, it is inferred that the limitations in the design of turbo codes provide a scope for improvement.

The code performance improved considerably by introducing third component in the conventional Turbo Codes. However, in [16] the magnitudes permeability and permutation standards seem to be static and these codes are unable to execute the desired result in various noise environments. In order to overcome this shortcoming, permeability rate and permutation rates are made dynamic in the noisy environment. Further, the computational complexity is also high in deriving third component codes. This is another bottleneck while analyzing with 3D EXIT chart analysis. Not much work has been done using any search algorithms.

The above shortcomings are resolved by introduction of adaptive parameters for third component. Thus, the code is termed as Adaptive Third Component Turbo Code (A3D-TC). The proposed A3D-TC enhanced the ability in improving error with the help of special intelligence (SI), that provides the permeability and permutation rate of third component encoder. The permeability and permittivity rates are made adaptive by using Genetic Algorithm based knowledge source and feeding it to feed forward neural network.

IV. Evolutionary Algorithms (EA)

In the early ages computers were used for defense purposes like deciphering the military code and tracking missiles and also for betterment of mankind which was possible by modeling the human brain, mimicking human learning and stimulating biological evolution. However these activities became insignificant over a period of time. But, the research community started prioritizing them from the early 1980's. The first advancement resulted into the growth of neural networks, machine learning as the second and the third being evolutionary computation which is well represented by Genetic Algorithm.

Evolutionary Algorithms are the most accepted and widely reached algorithms. They are non-traditional optimization techniques which mimic the process of evolution and correspond to biological systems which can be used in engineering. These algorithms form a group of iterative stochastic search and optimization methods, based on optimization strategies and operate with a population of artificial individuals. The objective function is carefully selected and used and the encoded (artificial) individuals are evaluated and a fitness value is assigned to each individual.

V. Genetic Algorithm (GA)

Genetic Algorithms are well known for finding minima within search spaces. They converge very quickly to these minimas. In GA the logic is based on natural selection and works on the concept of survival of the fittest. In this algorithm, successive generations become better and better.In numerical methods each generation is an iteration. For each generation there is progressive improvement. Robustness is the central theme of Genetic Algorithm. Efficiency and Efficacy are necessary for survival in different environments and a balance is to be achieved between the both by GA.

The main advantage of Genetic Algorithm is its convergence to global optima very fast, where many traditional algorithms fail to reach global optima. The main goal of optimization is to always keep on improving the performance to reach some optimal point. The GA's perspectives are:

- Priorities of optimization to be relooked.
- Most important goal for optimization is improvement

Efficiency and Efficacy are necessary for survival in different environments and a balance is to be achieved between the both by GA. However, Genetic Algorithms do suffer from some problems, such as premature convergence and slow convergence [5]. These issues can be resolved, to a certain extent, by tuning the parameters appropriately.

The main advantage of Genetic Algorithm over the many traditional algorithms is its super convergence to global optima. The main goal of optimization is to always keep on improving the performance to reach some optimal point.

The GA maintains a population of individuals which represents the set of solution candidates for the optimization problem to be solved. The goodness of each candidate solution is evaluated based on its fitness value. The population of the GAs evolves by a set of genetic operators. The basic genetic operators are selection, crossover and mutation. In the selection process, some individuals are selected to be copied into a tentative next population. Individual with higher fitness value is more likely to be selected. The selected individuals are altered by mutation and crossover and form a new population of solutions. The GAs is simple yet provides an adaptive and robust optimization methodology [9].

VI. CELL DESCRIPTION

Living organisms are made up of cells. Cells consist of the same set of one or more chromosomes. These are called strings of DNA. The chromosomes are made up of genes. These genes are functional blocks of DNA. Each of these genes encode a particular protein. The individual genes are located at a particular locus on the chromosome. All chromosomes put together are called as organisms' genome.

Genotype is a particular set of genes contained in genome. Any two individuals having similar genomes have same genotype. This genotype gives rise to phenotype where its mental characteristics, physical characteristics such as intelligence, attitude, brain size, height and color of hair or eyes undergo development.

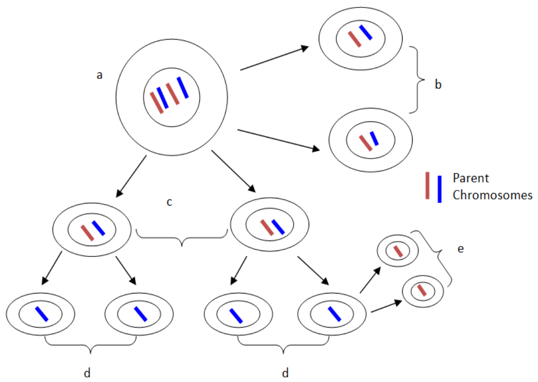

Figure: 3. Model of Genetic Algorithm

In Figure 3 the model of the genetic algorithm is shown. In this, 'a' represents the parent chromosome with the nucleus. It has two parent chromosomes and the duplication of them, totally four. One of the pairs goes to the child cells and this process is called Mitosis as shown in 'b'. Reproduction is a complicated process because the chromosomes get twisted up, break and then recombine. So the cells pull off from the main cell and gives rise to two more cells having two chromosomes each as in 'c'. These cells in turn split altogether into four cells and each in turn results in four cells of the parent as shown in 'd'. Under special occasions as in 'e' they may again split into another cell and give rise to an entirely new chromosome which may be called as new person. However there are lots of choices for the recombination.

Differences between GA's and other traditional optimization methods

- GA's work with the coding of the parameters set not the parameter themselves.
- GA's search for a Population of points not a single point.

- GA's use the objective function information and not the derivative or second derivative.
- GA's use probabilistic transition rules not deterministic rules.

VII. Basic Genetic Algorithm

- A trial solution is used which has a population of 2n to 4n (n represents number of variables).
- Corresponding to the chromosomes, each solution is usually represented by a string of binary (decimal can also be taken but binary is more preferable) variables in genetics.
- In order to achieve the desired accuracy, the string length can be increased as large as possible to achieve desired fitness.
- In genetics, the numerical value of objective function represents the concept of fitness.

Representation of Chromosomes

Chromosomes used in genetic algorithm can be represented as

- Bit strings
- Lists of rules
- Program elements (genetic programming)
- Real numbers
- Permutations of element
- Any other data structure

Based on the stochastic principles trial solutions are taken up and a new generation (a new set of strings) is formed where the children from the trial solutions are produced by the fittest parents. In this way, every child gets a portion of string from parents and generates new solutions.

GA's are widely used and highly successful variant of EA. Genetic operators implement GA via iterative application.

1. Initial Population
2. Fitness Function
3. Selection
4. Crossover
5. Mutation

Flowchart of Genetic Algorithm

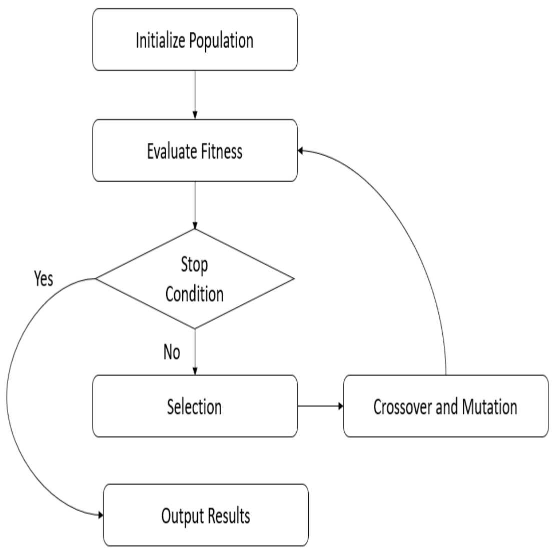

Figure 4: Flowchart for Genetic Algorithm

A. Initialization

Initial population begins with randomly generated states. The nature of the problem decides the population size and typically it may contain umpteen number of possible solutions. The randomly generated population is covered by the entire range of possible solutions (the search space).

As explained above, each organism in the genetic algorithm contains one chromosome and each chromosome can be considered as an individual or a solution possessing the parameters to be optimized.

B. Fitness Function

A random solution or collection of genes is initially assigned to each chromosome. This solution calculates the fitness level, which helps in determining the chromosome's suitability or fitness to survive. High level of fitness indicates that the chromosome has higher probability of mating and staying alive. The fitness function becomes the main criteria in producing the next generation of states. Based on the fitness function two individuals are selected. These individuals reproduce to give new offspring's which are mutated randomly. If it returns a better state, then it is termed as a good fitness function.

C. Mating

Mating helps to create a new and improved population in genetic algorithm. Suitability to mate depends on the chromosomes qualification criteria to mate, or the privilege to mate. The fitness of each chromosome determines the participation of the chromosome in mating. The children are produced from the chromosome selected from the old chromosome population and then mated. These new children add to the existing population. Chromosomes are selected from the updated population for the subsequent mating. Two parents are selected and a splice from each of their gene sequences is taken for mating.

However, this does not introduce any new genetic material into the population. Mutation is adopted to introduce new genetic material in population.

D. Mutation

Mutation is the process of introducing new genetic material into the population. It can be considered as natural experiment to bring in new, fairly random sequencesof genes into a chromosome. It may or may not produce desirable attribute. The natural selection determines the outcome of the mutated chromosome.

The mutated chromosomes will survive upon its higher fitness than the general population. Hence, only such perfectly fit chromosomes are allowed for further mating.

Different children having different characteristics result in this process. They are

Elite children best fitness values automatically survive and proceed to the next generation.

Crossover children are created by the combination of the vectors of a pair of parents.

Mutation children are the created by introduction of new genetic material into a single parent.

The following figure illustrates the type of children.

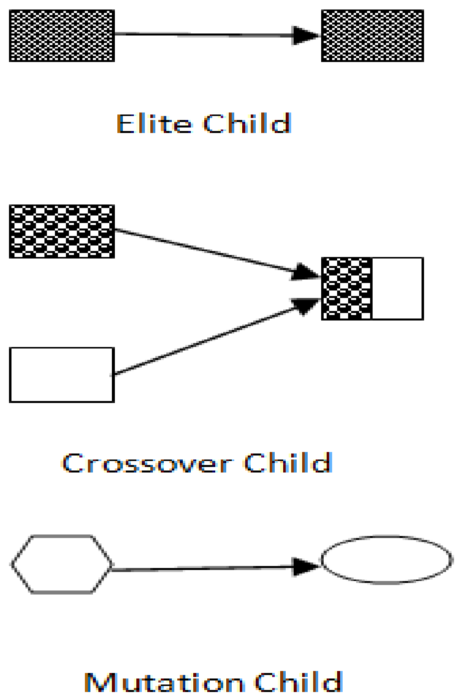

Figure: 5. Children from Genetic Algorithm

VIII. HOW GENETIC ALGORITHM WORKS

Genetic algorithm is initialized by composing an initial population consisting of chromosomes which comprise of a random collection of genes.

The steps involved are:

1. Creation of initial population of chromosomes.
2. The fitness/suitability of each chromosome is evaluated which is part of the population.
3. Depending on the fitness level, the chromosome qualified to mate or privileged to mate are selected.
4. Producing offspring.
5. Mutation.
6. Repeating steps three to five to create a new population.
7. For a preset number of generations, when the best solution has not changed, the algorithm ends.

IX. NEURAL NETWORKS

An Engineering Approach

Artificial Neuron

The first order characteristics of biological neuron are imitated in designing the artificial neuron. The device with multiple inputs and single output is called as an artificial neuron. It operates in two different modes, the training mode and using mode.

In training mode, the neuron is trained to decide to fire or not to fire based on the design of particular input.

In using mode, the current output is obtained when a taught input pattern is tracked at the input. In case of the absence of the input pattern in the taught list then the firing rule is employed to resolve whether to or not to fire.

The firing rule accounts for their high flexibility in neural networks and determines the calculation of whether a neuron should fire for the given input design. This applies to all input designs.

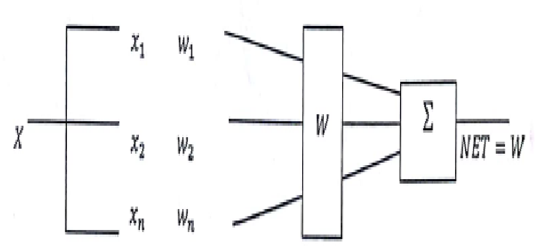

Figure: 6 Artificial Neuron

In the above Figure 6, x_1, x_2, …..,x_n are the inputs which are fed to artificial neuron. x_1, x_2, ….., x_n are referred as vector 'X' which corresponds to signal in the synapse of a biological neuron. These signals are multiplied by corresponding weight w_1, w_2, ….,w_n called as synaptic weights and summed in block Σ. Every weight corresponds to the strength of every biological synaptic connection. Vector 'W' is the outcome of the set of collective weights. The summation block is a replica of the biological cell body. It combines entire weight inputs generating NET as output. Vector notation of artificial neuron is NET = W

X. NEED FOR A3D-TC

The addition of third component [16] in conventional turbo codes proved to be extremely efficient in enhancing better code performance. But permeability and permutation rates do not vary with changing noise or they remain static in this three dimensional turbo codes. Hence they become challenging when working under different noisy environments.

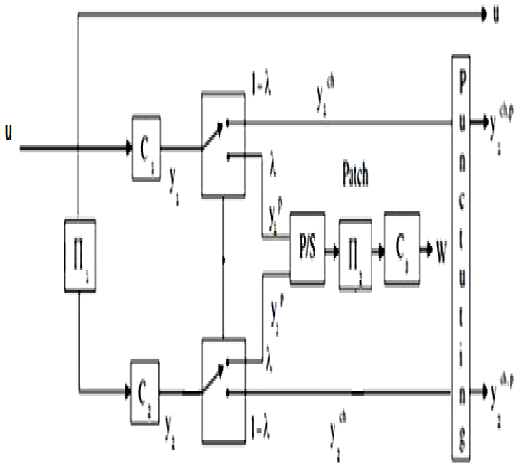

Figure: 7. Block diagram of the 3D-TC Encoder

So to overcome this, adaptive three dimensional turbo code(A3D-TC) is proposed to address the above mentioned constraints [16]. The A3D-TC encoder is shown in figure 8 and figure 9. Flexibility is attained in the parameters through Genetic Algorithm (GA) based knowledge source which is generated and fed to feed forward neural network. The network then generates third component parameters based on noise and signal strengths. This minimizes the bit error rate effectively while decoding.

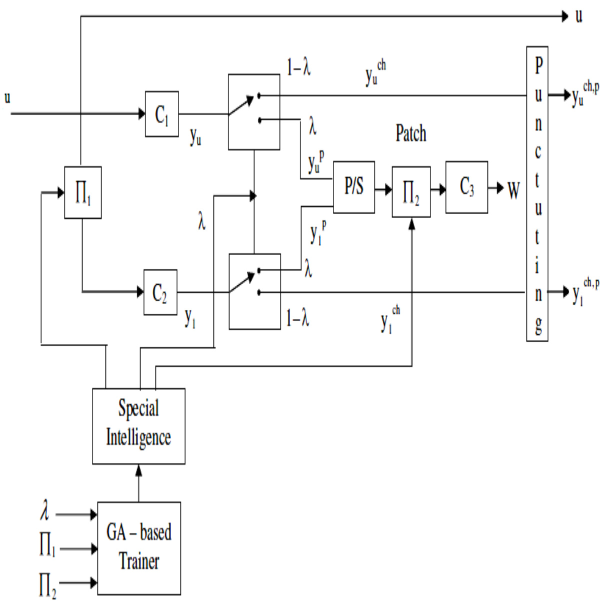

Figure: 8. A3D-TC Encoder

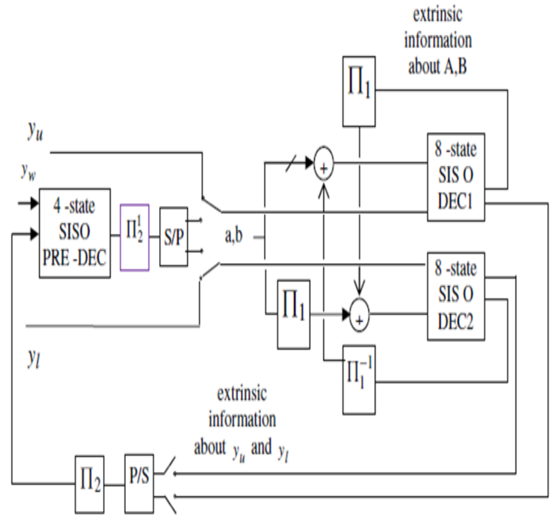

Figure: 9. A3D-TC Decoder

For different noisy environments, the results show that performance of A3D-TC is better when compared to conventional 3D -TC.

XI. Conclusion

Turbo Codes are a most important code used in the design of current communication systems. They provide close to optimal bit error rates at lesser signal to noise ratios for data transmission. They are vastly applied in wireless mobile communication systems because of their significant performance in minimization of end to end delay. Their performance can be further enhanced by the usage of a third component as it can attain better code performance. However, the bottleneck of this code is that permeability and permutation rates remain static and do not vary with channel noise which varies continuously. These codes cannot perform well at desired BER's for varying noise.

To overcome the above shortcomings, adaptive three-dimensional turbo code (A3D-TC) is proposed to further enhance the performance by resolving the above mentioned drawbacks. In A3D-TC, the parameters of third component are made adaptive by using Genetic Algorithm (GA) based knowledge source and feeding it to feed forward neural network by using special intelligence. The network then generates third component parameters namely permeability rate λ, permutation rate Π_1 and permutation rate Π_2 based on signal to noise ratio. Its performance is evaluated using different metrics. Further, the influence of NN structure on A3D-TC performance is analyzed by changing the size of hidden layer. Such varying parameters thus generated improved the error correction capability of the decoder and also minimized the bit error rate while decoding.

The proposed turbo code design is simulated in the working platform of MATLAB and the performance is evaluated and validated. The following conclusions are drawn from this research.

A3D-TC using GA has achieved minimum BER in majority of experiments. However, at a few instances of noisy environments A3D-TC has shown contrary result. The observations show that on an average, A3D-TC achieves a very good success deviations whereas the failure deviation is less when compared to 3D-TC.

The proposed solution offers better results due to the fact that the parameters in A3D-TC varying dynamically with channel conditions.

The effect of NN structure on the performance of A3D-TC is evaluated by changing the size of hidden layer. The error rate improved because of the genetic algorithm. A3D-TC using Genetic algorithm is performing better because of the nature of experimental results such as (i) achieving minimal BER when increasing network complexity and (ii) lesser failure deviation and higher success deviation.

REFERENCES:

[1] Farhan Aadil, Shahzada Khayyam Nisar, Wajahat Abbas and Asim Shahzad, “Reusable IP core for Forward Error Correcting Codes”, International Journal of Basic & Applied Sciences IJBAS-IJENS, Vol.10, No.01, pp.24-30.

[2] Joanne Gomes and B K Mishra, “Double Error Correcting Long Code”, International Journal of Computer Networks & Communications (IJCNC), Vol.2,No.5, pp.58-69, 2010, DOI : 10.5121/ijcnc.2010.2504

[3] R.W. Hamming, “Error detecting and error correcting codes”, The BELL system technical journal, Vol.29, No.2, pp.1-14,1950.

[4] Burr A., “Turbo-codes: the ultimate error control codes?”, Electronics & Communication Engineering Journal, Vol.13, No.4, pp.155 – 165,2001.

[5] Said M. Elnoubi, Shawky E. Shabaan and Ahmed H Abd El-Malek, "New Trend in Space Time Error Correcting Codes”, Journal of Selected Areas in Telecommunications (JSAT),pp.32-39, March Edition, 2011

[6] G. A. Lazar, N. R. Buzatu, E. Cojocariu and L. Trifina, "New Deterministic Code Matched Inter leaver For Turbo codes”, Journal of Theoretical and Applied Information Technology, Vol.10 , No2., pp.89-93, 2005 – 2009.

[7] Hamood Shehab and Widad Ismail, “The Development & Implementation of Reed Solomon Codes for OFDM Using Software-Defined Radio Platform”, International Journal of Computer Science & Communication,

Vol. 1, No. 1, pp. 129-136,2010

[8] Satoshi Yamazaki and David K. Asano, "A Serial Unequal Error Protection Code System Using Multilevel Trellis Coded Modulation with Ring-type Signal Constellations for AWGN Channels", IEEJ transactions on electrical and electronic engineering, Vol. 5,No.6, pp.708–716, 2010,doi:10.1002/tee.20596

[9] Daniel J. Costello, Joachim Hagenauer, Hideki Imai and Stephen B. Wicker, "Applications of Error-Control Coding", IEEE Transactions on Information Theory, Vol. 44, No. 6, pp.2531-2560,1998

[10] Chih-Heng Ke, Rung-Shiang Cheng, Chen-Da Tsai and Ming-Fong Tsai, "Bandwidth Aggregation with Path Interleaving Forward Error Correction Mechanism for Delay-Sensitive Video Streaming in Wireless Multipath Environments", Tamkang Journal of Science and Engineering, Vol. 13, No. 1, pp.1-9 ,2010.

[11] Ojo, F. K. and Ogunti, E. O., "Investigation of Carrier-Phase Offsets in Digital Passband Communication Systems for QPSK Gray-Encoding using Constant-Phase and Random-Walk Phase Models", European Journal of Scientific Research, Vol.57, No.3 pp. 454-465, 2011.

[12] Eyas El-Qawasmeh, Maytham Safar and Talal Kanan, "Investigation of Golay Code (24, 12, 8) Structure in Improving Search Techniques", The International Arab Journal of Information Technology, Vol. 8, No. 3, pp. 265-271,2011

[13] Lee, J. W., Urbanke, R. L. and Blahut, R. E., "Turbo Codes in Binary Erasure Channel", IEEE Transactions on Information Theory, Vol.54 , No.4, pp.1765 – 1773, 2008.

[14] Berrou, C., Graelli Amat, A., Ould-Cheikh-Mouhamedou, Y. and Saouter, Y., "Improving the Distance Properties of Turbo Codes Using a Third Component Code: 3D Turbo Codes", IEEE Transactions on Communications, Vol. 57, No.9, pp. 2505–2509, 2009.

[15] Babich, F., Crismani, A. and Maunder, R. G., "EXIT Chart Aided Design of Periodically Punctured Turbo Codes", IEEE Electronics Letters, Vol. 46, No. 14, 2010

[16] Suman Kshirsagar and E. Nagabhooshanam , "The A3D-TC: An adaptive Approach for selecting third component parameters to generate Robust Turbo Codes," International Journal of Computer Applications, vol. 52-No.21, August 2012.

* * * * *