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Validation of Heuristic Algorithms for improved BER performance

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ABSTRACT:*The performance of the code was improved effectively by introducing the third component in conventional turbo codes. But their adaptability to the varying noise environments was very poor. This degraded their performance in achieving the low bit error rates. To overcome the aforesaid drawback Adaptive third dimension turbo code was proposed in our previous paper [1]. The parameters were made adaptive by generating genetic algorithm based knowledge source. In [2] comparison was made between Genetic algorithm and Simulating Annealing algorithm. In this paper the performance analysis and validation is done between these two algorithms. The analysis showed that genetic algorithm is able to give better performance when compared to simulated annealing algorithm.*

KEYWORDS: *Knowledge feeding, Adaptability, Genetic algorithm, Simulated Annealing, error rates, third component, Turbo codes.*

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I. INTRODUCTION

To withstand the effects of various channel impairments such as noise, interference and fading channel coding is done which improved communication performance. Channel coding is divided as waveform coding and structured sequences. Waveform coding deals with transforming waveforms into better waveforms to make the detection process less subject to errors. Structured sequences deals with transforming data sequences into better sequences having structured redundancy. The detection and correction of errors is done by these redundant bits.
A major concern in digital communication therefore is to develop error correcting technique that covers the gap be-tween the performance of practical communication systems and the ideal channel capacity.
Forward Error Correction codes (FEC) or channel codes have become inevitable [3] to get the desired quality of service over a link in wireless based digital communication systems. This helps the system to operate at lower signal to noise ratio within a transmit power or gain thereby achieving the desired quality of service.The use of FEC codes in communication system is an integral part of ensuring reliable communication [4].
In mid 90's when Turbo code was introduced, it marked the beginning of a lot of research work addressing the analysis, design and application of iterative decoding in digital communication [5]. Turbo codes performance is very close to the limit of Reliable communication given by Shannon Limit. It has also been proved that these codes offer remarkable performance over low SNR domains. They achieve a bit error probability of 10^{-5}, using a rate ½ code over an AWGN channel at $Eb/N0$ of 0.7dB.

II. the adaptive third component turbo codes(a3d-tc)

The error correction capability is improved to a certain extent by the proposed A3D-TC by generating the special intelligence (SI), where the permeability and permittivity rate of the third component encoder is decided. Tuning is done by generating knowledge source and then by knowledge feeding using both Genetic Algorithm and Simulated Annealing Algorithm. Once tuning is completed the third component parameters are generated dynamically according to the noise variance. The block diagram of A3D-TC encoder and decoder for the heuristic algorithms is given in Fig: 1 and 2.

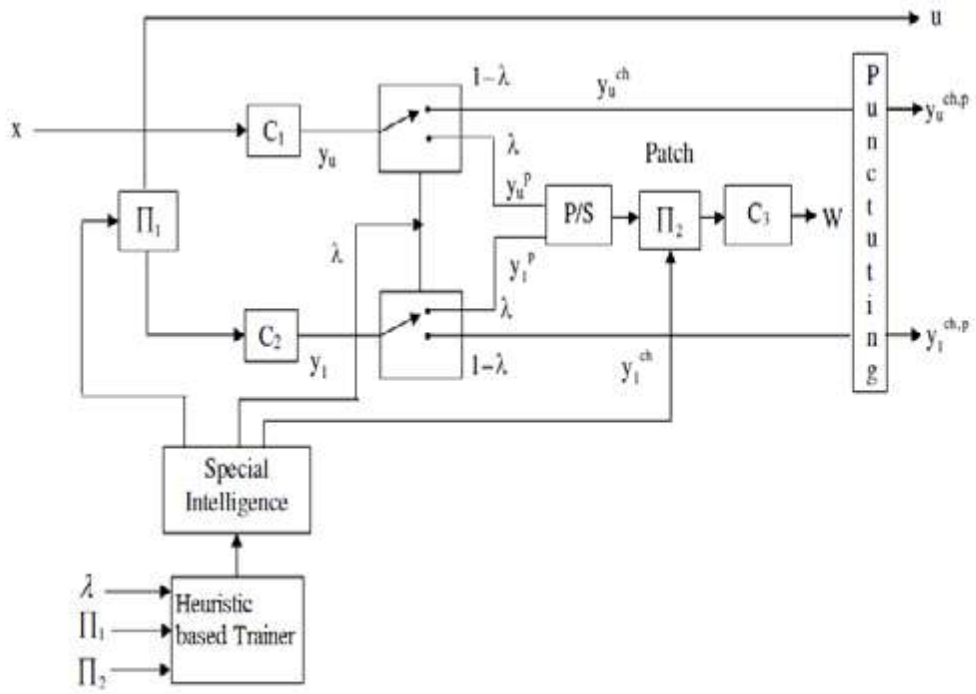

Figure 1: Proposed A3D-TC Encoder

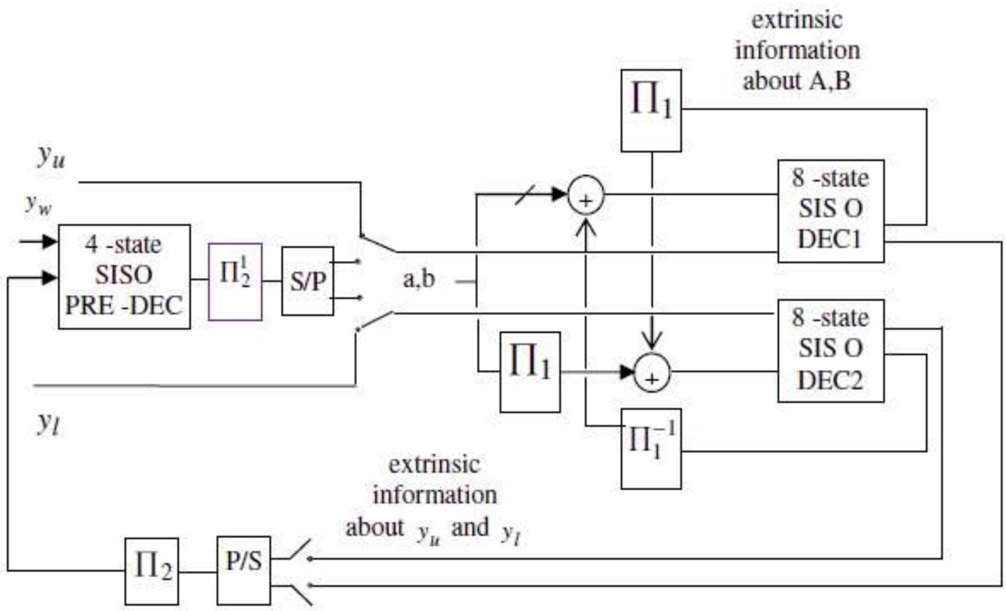

Figure 2: Proposed A3D-TC Decoder

The special intelligence added to the third component of the encoder never disturbed the conventional third component decoder [6], which is given in Fig: 2.

III. GENETIC ALGORITHM(GA)

Genetic algorithm starts by creating an initial population consisting of chromosomes to which a random collection of genes are given. Genetic algorithms strive to determine the optimal solution to a problem by utilizing three genetic operators. The operators include selection, crossover, and mutation. Its search for the optimal solution until specific criteria are met and then the process terminates. The results of the process include good solutions, as compared to one “optimal” solution, for complex problems.

IV. SIMULATED ANNEALING ALGORITHM (SA)

Simulated Annealing is developed to optimize the design of IC chips by simulating the actual process of annealing. It is an iterative procedure that continuously updates one candidate solution until a termination condition is reached. This algorithm is used for combinatorial optimization problems, where functions are minimized of very many variables. The training of the special intelligence is done using simulated annealing algorithm. This is done by generating a precise training dataset, as was done for Genetic Algorithm.

Simulated Annealing (SA) is a probabilistic method for finding the global optima of a cost function, proposed in it [7]. It is basically an imitation of the annealing process in which a liquid freezes so that when the structure settles down, it has a minimum energy configuration.

The main advantage of SA is that it avoids local minima (or optima) by “jumping” from the current solution to a point in the neighborhood. The probability of this jump depends on the value of the cost function at the current solution and the neighbor and also on the temperature value. The temperature function is to be selected such that at the initial stages, these jumps are to be relatively frequent compared to the later stages, when the structure cools down.

V. IMPLEMENTATION RESULTS

The proposed A3D-TC is implemented and validated in the working platform of MATLAB (version 7.12).The comparison is done over A3D-TC using both Genetic Algorithm and Simulated Annealing Algorithm for various noise variances. A3D-TC is evaluated for different ANN structures by varying NH as 20, 30 and 40 to analyze the influence of network structure in TC performance [2]. Ten experiments are carried out for every structure and the results are presented in the Table 1.

Table 1: BER performance of A3D-TC implemented using Genetic Algorithm(GA) and Simulated Annealing Algorithm(SA) with network structure having (i) 20 hidden neurons, (ii) 30 hidden neurons and (iii) 40 hidden neurons for different noise variances from different rounds of experiments

20 Neurons

Experiment No.	Noise							
	0.15		0.25		0.35		0.45	
	GA	SA	GA	SA	GA	SA	GA	SA
1	0.15	0.134	0.104	0.121	0.074	0.121	0.027	0.103
2	0.07	0.135	0.141	0.113	0.137	0.103	0.059	0.082
3	0.128	0.145	0.101	0.121	0.074	0.115	0.018	0.086
4	0.116	0.110	0.128	0.124	0.121	0.102	0.134	0.103
5	0.121	0.117	0.114	0.136	0.119	0.111	0.107	0.120
6	0.141	0.148	0.163	0.133	0.064	0.117	0.026	0.109
7	0.110	0.135	0.058	0.126	0.057	0.115	0.050	0.110
8	0.118	0.115	0.077	0.126	0.088	0.115	0.042	0.110
9	0.143	0.128	0.087	0.115	0.060	0.104	0.085	0.103
10	0.149	0.123	0.085	0.116	0.180	0.102	0.036	0.065

30 Neurons

Experiment No.	Noise							
	0.15		0.25		0.35		0.45	
	GA	SA	GA	SA	GA	SA	GA	SA
1	0.109	0.113	0.127	0.108	0.111	0.109	0.024	0.080
2	0.132	0.130	0.114	0.117	0.086	0.085	0.040	0.101
3	0.142	0.140	0.054	0.116	0.091	0.080	0.023	0.064
4	0.173	0.141	0.118	0.119	0.140	0.119	0.042	0.107
5	0.131	0.125	0.061	0.122	0.108	0.130	0.057	0.099
6	0.064	0.136	0.129	0.137	0.085	0.113	0.078	0.106
7	0.097	0.133	0.121	0.125	0.151	0.118	0.060	0.103
8	0.118	0.148	0.121	0.134	0.102	0.089	0.018	0.101
9	0.155	0.127	0.102	0.120	0.112	0.109	0.146	0.109
10	0.071	0.141	0.061	0.120	0.067	0.134	0.054	0.064

40 Neurons

Experiment No.	Noise							
	0.15		0.25		0.35		0.45	
	GA	SA	GA	SA	GA	SA	GA	SA
1	0.123	0.133	0.158	0.131	0.111	0.101	0.027	0.092
2	0.150	0.151	0.075	0.124	0.086	0.108	0.014	0.109
3	0.111	0.131	0.128	0.138	0.091	0.106	0.154	0.117
4	0.132	0.142	0.116	0.134	0.040	0.103	0.018	0.093
5	0.101	0.121	0.125	0.125	0.108	0.109	0.161	0.101
6	0.126	0.135	0.144	0.137	0.185	0.119	0.029	0.089

7	0.151	0.119	0.010	0.121	0.151	0.107	0.121	0.104
8	0.144	0.135	0.018	0.142	0.102	0.102	0.012	0.086
9	0.115	0.128	0.147	0.130	0.021	0.115	0.002	0.096
10	0.102	0.125	0.106	0.128	0.033	0.107	0.067	0.109

Table: 2. Average Performances of GA and SA

20 Neurons

	0.15	**0.25**	**0.35**	**0.45**
SA	0.129	0.1231	0.1105	0.0991
GA	0.1246	0.1058	0.0974	0.0584

30 Neurons

	0.15	**0.25**	**0.35**	**0.45**
SA	0.1334	0.1218	0.1086	0.0934
GA	0.1192	0.1008	0.1053	0.0542

40 Neurons

	0.15	**0.25**	**0.35**	**0.45**
SA	0.1334	0.131	0.1077	0.0996
GA	0.1255	0.1027	0.0928	00605

The performance of GA is found to be better compared to SA at the average values of 20, 30 and 40 neurons for noise variances 0.15, 0.25, 0.35, and 0.45. This is elaborated as follows:

20 Neurons

N_σ	**Difference**
0.15	0.0044
0.25	0.0173
0.35	0.0131
0.45	0.0407

From the table it is observed that GA achieves overall average of 0.018875 success deviation when compared to SA for network complexity of 20 neurons.

30 Neurons

N_σ	**Difference**
0.15	0.0142
0.25	0.021
0.35	0.0033
0.45	0.0392

From the table it is observed that GA achieves overall average of 0.019425 success deviation when compared to SA for network complexity of 30 neurons.

40 Neurons

N_σ	**Difference**
0.15	0.0079
0.25	0.0283
0.35	0.0149
0.45	0.0391

From the table it is observed that GA achieves overall average of 0.02255 success deviation when compared to SA for network complexity of 40 neurons.

VI. CONCLUSIONS

The proposed solution offers better results due to the fact that the parameters in A3D-TC varying dynamically with channel conditions. In this technique, Genetic Algorithm with Simulating Annealing (SA)are applied to A3D-TC and their results are compared.

It is observed that GA achieves overall average of 0.019425success deviation with zero failure deviation when compared to SA for network complexity of 20 neurons. For 30 neurons GA achieves 0.019425success deviation andzerofailure deviationcompared to SA. For network complexity of 40 neurons GA achieves overall average of 0.02255 success deviation with zero failure deviation when compared to SA.

REFERENCES

[1]. Suman Kshirsagar and Dr. E.Nagabhooshanam ,"The A3D-TC: An adaptive Approach for selecting third component parameters to generate Robust Turbo Codes," International Journal of CompuerApplicatios, vol. 52- No.21, August 2012.
[2]. Suman Kshirsagar and Dr. E.Nagabhooshanam , " Performance of Heuristic Algorithms in minimizing BER for Robust Turbo Codes",International Journal of Scientific & Engineering Research, Volume 4, Issue 5, May-2013 1607 ISSN 2229-5518
[3]. FarhanAadil, Shahzada Khayyam Nisar, Wajahat Abbas and AsimShahzad, "Reusable IP core for Forward Error Correcting Codes", International Journal of Basic &Ap-plied Sciences IJBAS-IJENS, Vol.10, No.01, pp.24-30
[4]. HamoodShehab 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
[5]. Ojo, F. K. and Ogunti, E. O., "Investigation of Carrier-Phase Offsets in Digital Passband Communication Sys- tems 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.
[6]. C.Berrou, A.GraellI.Amat, Y.OuldCheikhMouhamedou, C. Douillard, Y. Saouter, "Adding a Rate-1 Third Di- mension to Turbo Codes", IEEE Information Theory Workshop, Pages: 156-161, 2007
[7]. Kirkpatrick, S., C. D. Gelatt Jr., M. P. Vecchi, Optimization by Simulated Annealing, Science, 220, 4598, 671- 680 (1983) and Cerny, V., Thermodynamically Approach to the Travelling Salesman Problem.

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