Scientific Journal Impact Factor (SJIF): 1.711
International Journal of Modern Trends in Engineering and Research
ISSN (ONLINE) : 2349 - 9745 ISSN (PRINT) : 2393 - 8161

Fir Filter Design Using Optimization Implementation Using VHDL

Yogeshwari mahanti[1], Chandrahas sahu[2]
[1,2]*Electronics and telecommunication, SSCET*

Abstract— In recent years a very intensive research work is concerned with design of digital filters. The filter shave two uses: signal separation and signal restoration. Signal separation is needed when a signal has been contaminated with interference, noise, or other signals. Signal restoration is required when a signal has been distorted in some way. Every linear filter has an impulse response, a step response and a frequency response .Each of these responses contains complete information about the filter, but in a different form. The filter design process can be described as an optimization problem where each requirement contributes with a term to an error function which should be minimized. Classical optimization methods cannot optimize such objective functions and cannot converge to the global minimum solution. To reduce all these drawbacks encountered with the classical optimization methods, several researchers have utilized many heuristic and meta-heuristic evolutionary optimization algorithms, the majority of which are based on the natural selection and evolution technique. A new algorithm binary discrete optimization method based on cat swarm optimization (CSO). BCSO is a binary version of CSO generated by observing the behaviors of cats. As in CSO, BCSO consists of two modes of operation: tracing mode and seeking mode. The obtained results are compared with a number of different optimization problems including genetic algorithm and different versions of binary discrete particle swarm optimization is the best. It is shown that the proposed method greatly improves the results obtained by other binary discrete optimization problems**.**

Keywords— Digital filter, PSO, GA, CSO, BCSO

I. INTRODUCTION

Digital Signal Processing (DSP) is one of the most powerful technologies that are shaping science and engineering in the twenty-first century. Revolutionary changes have already been made in a broad range of fields: communications, medical imaging, radar and sonar, and high fidelity music reproduction, to name just a few. Each of these areas has developed a comprehensive DSP technology, with its own algorithms, mathematics, and specialized techniques. Analog (electronic) filters can be used for these tasks, as these are cheap, fast, and have a large dynamic range in both amplitude and frequency; however, digital filters are vastly superior in the level of performance. In this work, a type of digital filter i.e., FIR filter is used to separate one band of frequencies from another.

Filters designed by the GA have the potential of obtaining near global optimum solution. Although standard GA (also known as Real Coded GA (RGA)) shows a good performance for finding the promising regions of the search space, they are inefficient in determining the global optimum in terms of convergence speed and solution quality. In order to overcome the problem associated with RGA ,orthogonal genetic algorithm(OGA) , hybrid Taguchi GA(TGA) have been proposed. Adaptive Differential Evolution (ADE) , Differential cultural algorithm , Particle Swarm Optimization (PSO) , some variants of PSO like Quantum PSO (QPSO) , PSO with Quantum Infusion(PSO-QI) , Adaptive inertia weight PSO , Craziness PSO (CRPSO) , Gravitation search algorithm(GSA) , Seeker Optimization Algorithm(SOA) , some hybrid algorithm like DE–PSO have also been applied for filter design problems.

A new algorithm binary discrete optimization method based on cat swarm optimization (CSO). BCSO is a binary version of CSO generated by observing the behaviors of cats. As in CSO, BCSO consists of two modes of operation: *tracing mode* and *seeking mode*. The BCSO implemented on a number of benchmark optimization problems and zero-one knapsack problem. The obtained results are compared with a number of different optimization problems including genetic algorithm and different versions of binary discrete particle swarm optimization. It is shown that the proposed method greatly improves the results obtained by other binary discrete optimization problems. The difference between the BCSO and CSO is that the parameters of BCSO can take the values of *zero* and *one*, this makes the algorithm totally difference. The velocity of CSO in tracing mode changes its meaning to probability of change in the bits in BCSO. The proposed BCSO is tested in a number of different benchmark optimization problems and on binary knapsack problem. The results are compared with those of genetic algorithm, BPSO and NBPSO . The results shows that the proposed method highly outperform above mentioned algorithms.

II. THE PROPOSED BINARY DISCRETE CAT ALGORITHM

This method based on the CSO algorithm, a novel discrete binary optimization algorithm is proposed. Different from the continuous version of CSO, in BCSO the position vector is composed of ones and zeros. This change produces some major differences between CSO and BCSO. Similar to the continuous version of CSO, BCSO is composed of two modes: seeking and tracing.

1. Seeking mode

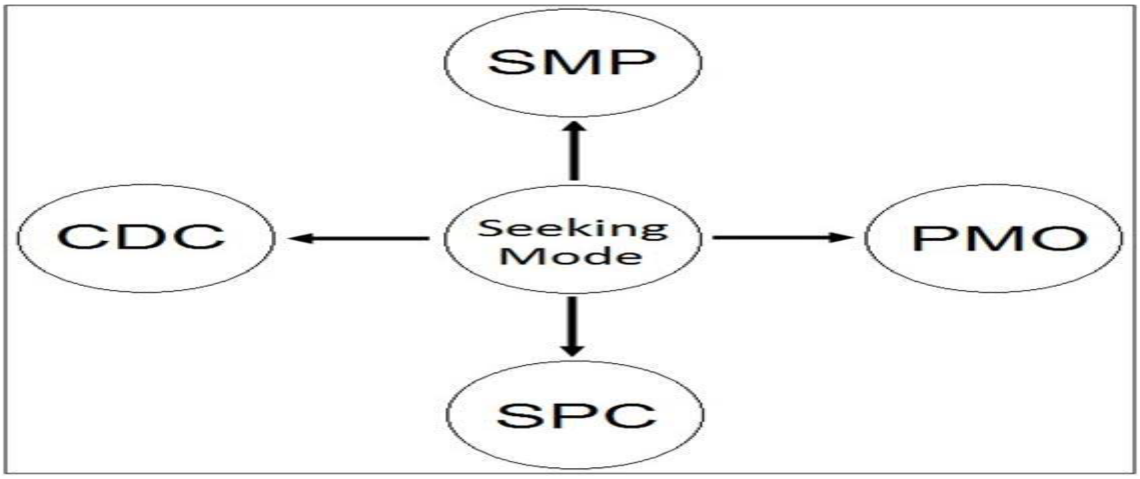
Much like what happens in the continuous version of CSO, the seeking mode of BCSO models the cats in the resting mode by introducing slight changes to the current position of each cat in the swarm. In Seeking Mode of BCSO, four essential factors are defined as in Fig. 1. Since all of the values in BCSO are zero and one change in the current position of a cat can be defined as a binary mutation. In this case, the parameter probability of mutation operation (PMO) replaces the parameter SRD in the original version of the CSO. The other parameters of CSO are exactly the same as continuous version of CSO. Much like the seeking mode of CSO, BCS has also 5 steps as follows.

Step 1: If SPC flag is *true* it means that the original position of the cat*k* can be a possible candidate so we need additional SMP-1 copies of the present position of each cat and take the current position as one of the candidates. But if SPC flag is *not true* make SMP copies of the present position of each cat.

Step 2: This step is the main difference between the BCSO and CSO. For each of SMP copies, select as many as CDC dimensions and randomly mutate this CDC dimensions according to PMO and replace the old ones. As can be seen from this step since the values of BCSO are binary, SRD changes to probability of mutation PMO.

Step 3: Considering the cost function, find the fitness values (FS) of all candidate points.

Volume 02, Issue 11, [November – 2015] ISSN (Online):2349–9745 ; ISSN (Print):2393-8161



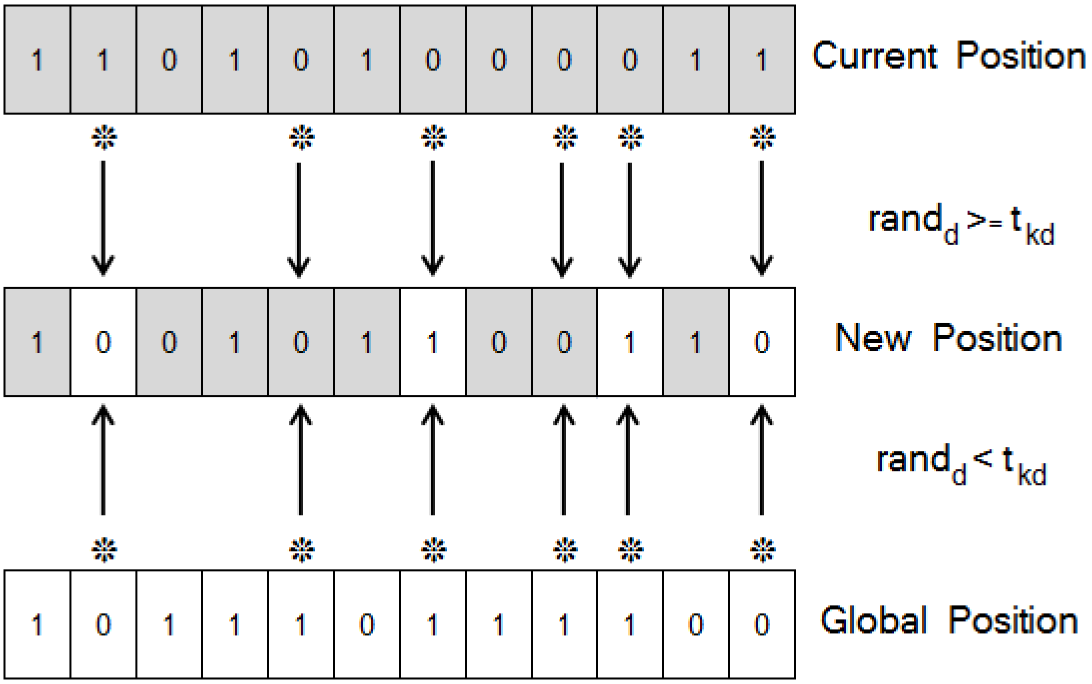
.
Step 4: If it happens that fitness values are exactly the same, assign a similar probability to all of the candidates, else calculate the selecting probability of each candidate point according to the following equation.

$$Pi = \frac{\mathrm{FSi} - \mathrm{FSb}}{\mathrm{FSmax} - \mathrm{FSmin}}$$

In which *FSb* = *FSmax* for finding the minimum solution and *FSb* = *FSmin* for finding the maximum solution.
Step 5: Apply roulette wheel to the candidate points, select one candidate and replace the current position with the selected candidate.

2. Tracing Mode

Similar to what happens in CSO, in the tracing mode of BCSO, cats are moving towards the best target. The main difference between CSO and BCSO is in the definition of velocity. In CSO velocity defines the difference between the current and previous position of a cat, but in BCSO the velocity vector changes its meaning to the probability of mutation in each dimension of a cat. The velocity vector which is now changes its meaning to probability of change is updated as follows. Two velocity vector one for each cats are defined as $V1kd$ and $V0kd$. $V0kd$ is the probability of the bits of the particle to change to zero while $V1kd$ is the probability that bits of particle change to one. Since in update equation of these velocities, which will be introduced later, the inertia term is used, these velocities are not complement.



The update process of $V1kd$ and $V0kd$ are as follows.
$V1kd = wV1kd + d1kd$
$V0kd = wV0kd + d0kd \quad d = 1, ...,M$
in which $d1kd$ and $d0kd$ are updated as in .
$i\, f\, Xgbest,d = 1 Then d1kd = r1c1$ and $d0kd = -r1c1$
$i\, f\, Xgbest,d = 0 Then d1kd = -r1c1$ and $d0kd = r1c1$

in which $r1$ has a random values in the interval of [0,1], w is the inertia weight and $c1$ is a constant which is defined by the user. According to current position cat$k$, the velocity of cat$k$ is calculated as:

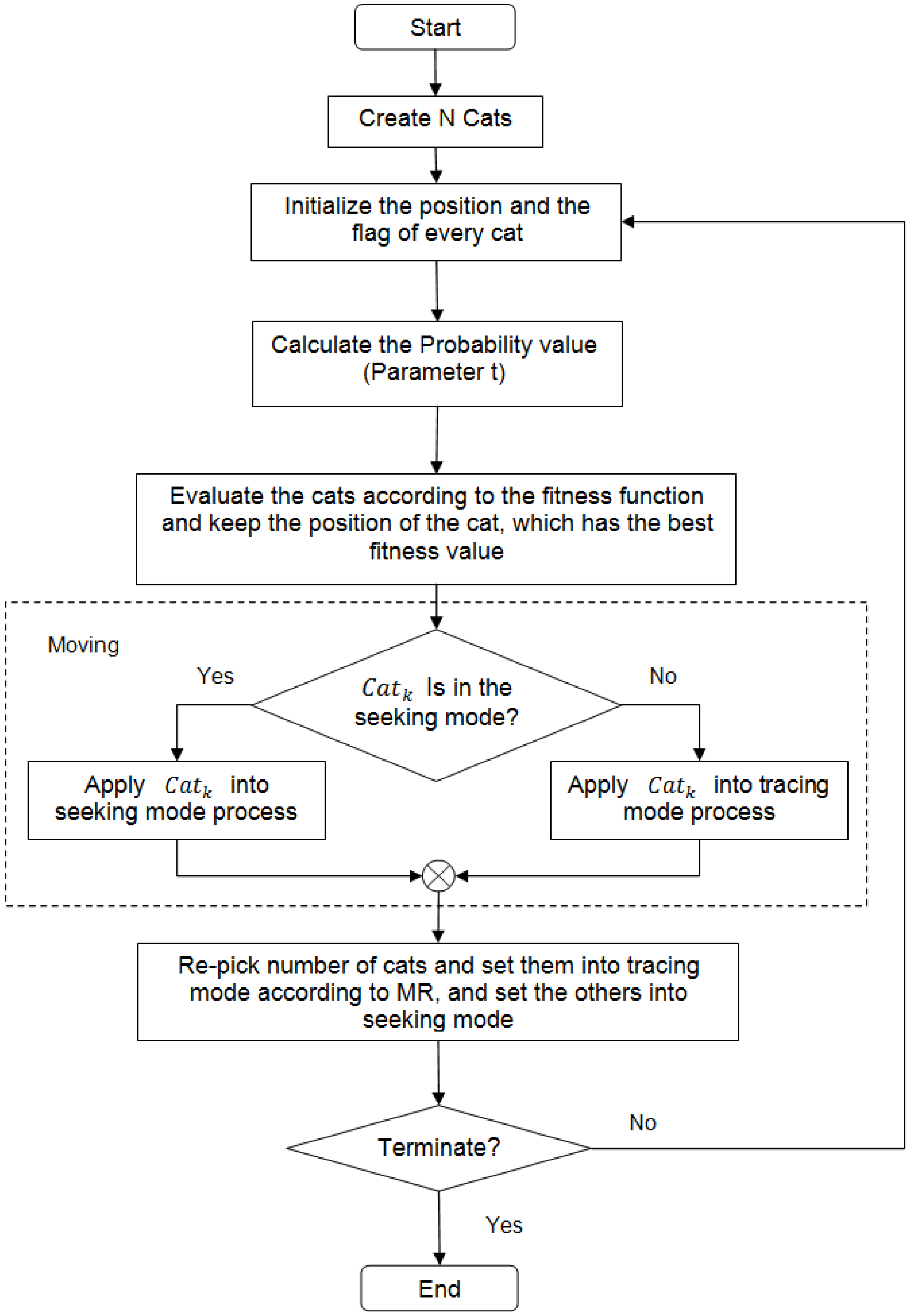
$V'kd =\{V1kd$ if $Xkd = 0$
$V0kd$ if $Xkd = 1$

The probability of mutation in each dimension is defined by the parameter t which is calculated using the following equation.

$tkd = sig(V'kd) =1$
$1+e-V'kd$

In which tkd takes a value in the interval of [0, 1]. Based on the value of tkd the new position of each dimension of cat is updated as follows.
$xkd =\{Xgbest,d$ if $rand < tkd$
xkd if $tkd < rand \quad d = 1, ...,M$

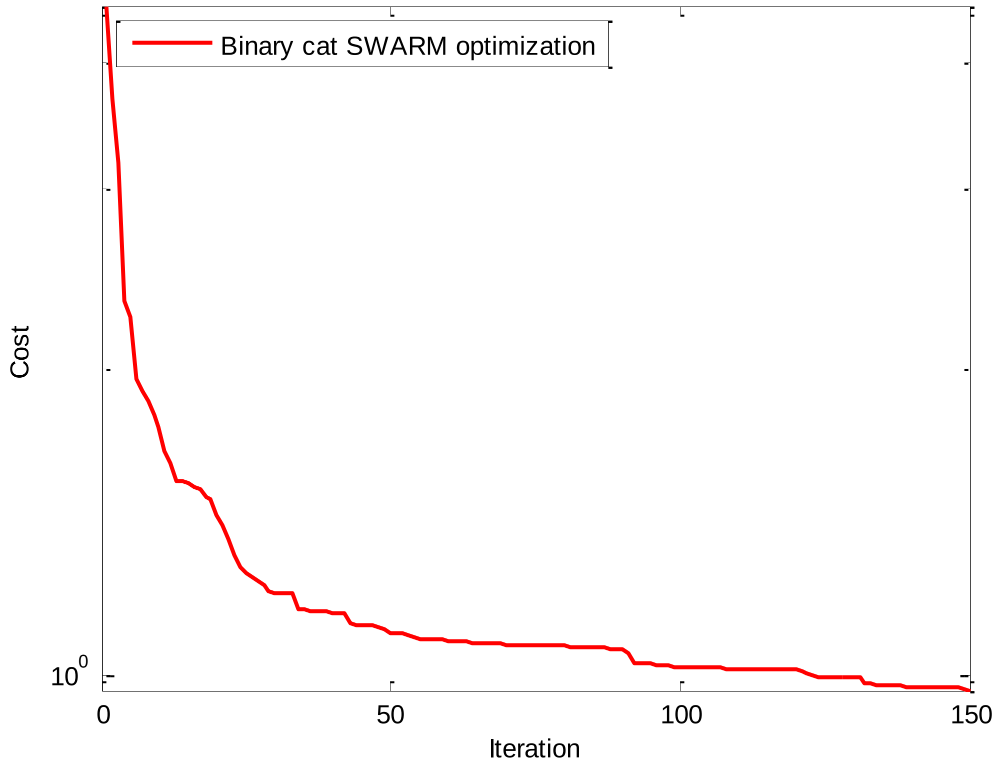
It should be noted that the maximum velocity vector of $V'kd$ should be bounded to a value $Vmax$. If the value of $V'kd$ becomes larger than $Vmax$, $Vmax$ should be selected for velocity in the corresponding dimension. Fig depicts the flowchart of BCSO.

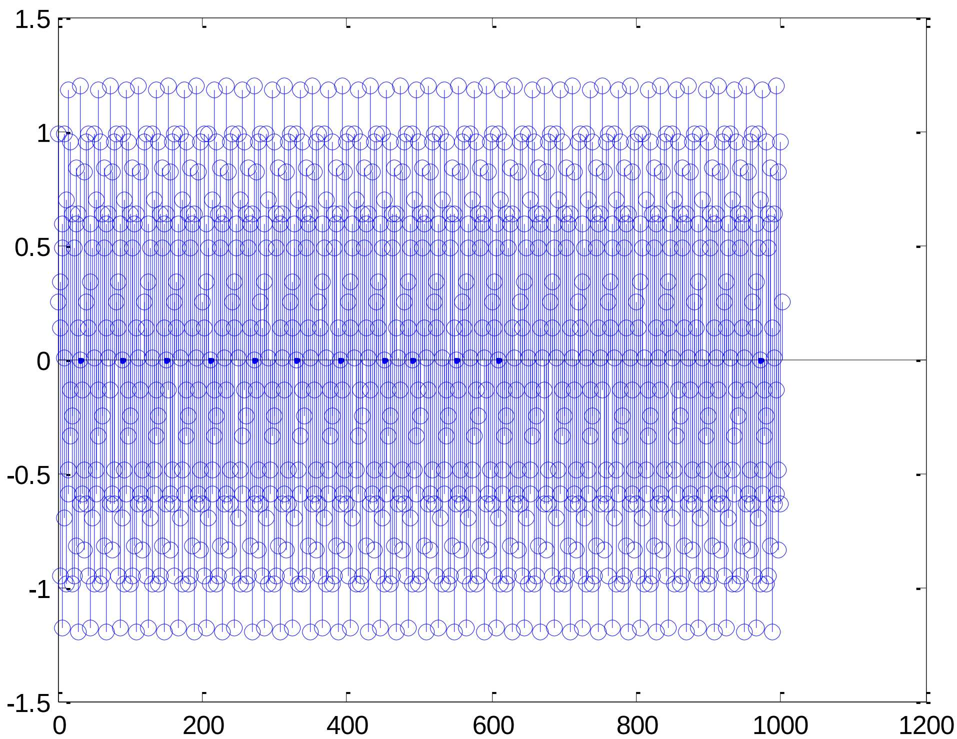

Start
Create N Cats
Initialize the position and the flag of every cat
Calculate the Probability value (Parameter t)
Evaluate the cats according to the fitness function and keep the position of the cat, which has the best fitness value
Moving
Yes
Cat_k Is in the seeking mode?
No
Apply Cat_k into seeking mode process
Apply Cat_k into tracing mode process
Re-pick number of cats and set them into tracing mode according to MR, and set the others into seeking mode
Terminate?
No
Yes
End

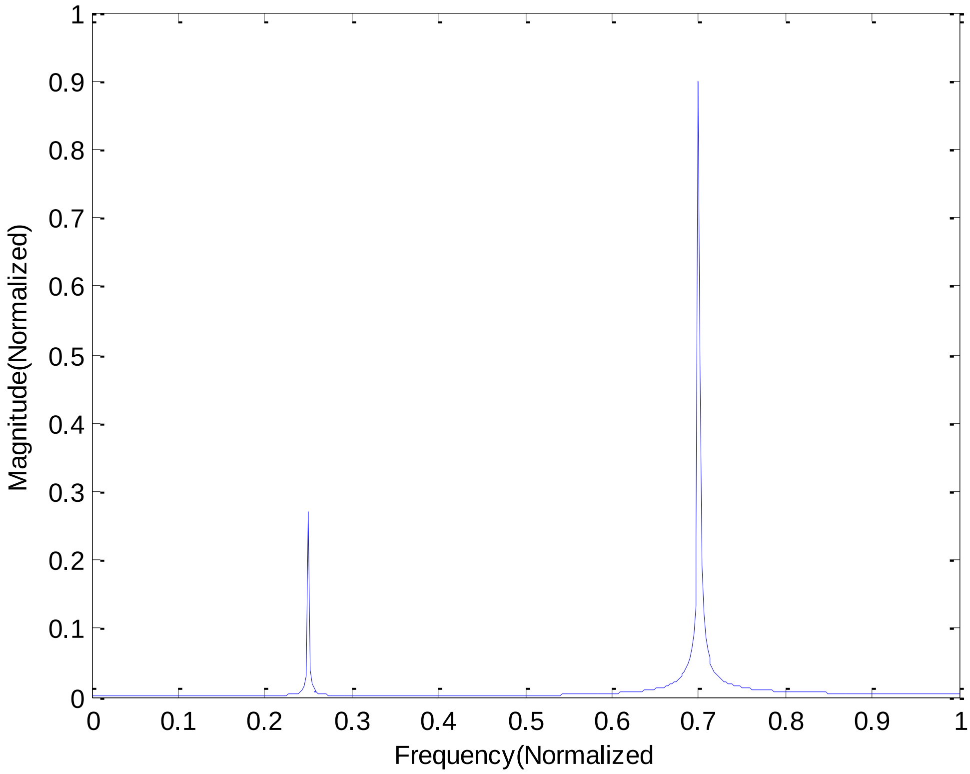
Volume 02, Issue 11, [November – 2015] ISSN (Online):2349–9745 ; ISSN (Print):2393-8161

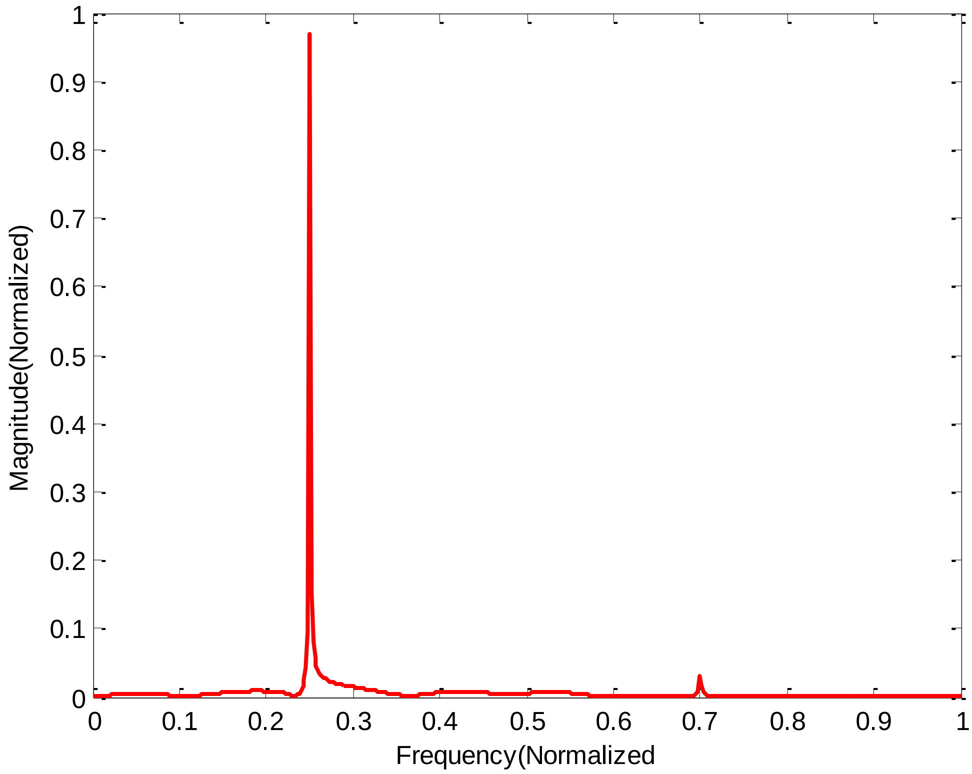
III. RESULT

COMPARISION BETWEEN IDEAL FILER AND BINARY CAT SWARM OPTIMIZATION






Magnitude(Normalized)
Frequency(Normalized
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1


Magnitude(Normalized)
Frequency(Normalized
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

IV. CONCLUSION

A new binary discrete optimization algorithm based on behavior of group of cats is presented. In binary discrete optimization problems the position vector are binary *zero* and *one* values. This causes significant change in BCSO with respect to CSO. In fact in BCSO in the seeking mode the slight change in the position takes place by introducing the mutation operation. The interpretation of velocity vector in tracing mode also changes to probability of change in each dimension of position of the cats. The proposed BCSO is implemented and tested on zero-one knapsack problem and a number of different benchmark problems. The obtained results are compared with that of BPSO, NBPSO and GA. The simulation results shows the proposed method greatly outperforms the above mentioned algorithms in terms of accuracy of the obtained results and speed of convergence.

REFERENCES

[1] K.D.Underwood and K.S. Hemmert ,"Closing the Gap : CPU and FPGA Trends in Sustainable Floating -point BLAS Performance ," presented at International Symposium on Field-programmable Custom computing machines , California ,USA , 2004.
[2] L.Zhuo and V.K.Prasanna, "Sparse Matrix-Vector Multiplication on FPGA, "presented at international symposium on Field Programmable Gate Arrays (FPGA) , Monterey ,CA , 2005.
[3] Y.Meng ,A.P.Brown , R.A.Iltis , T.Sherwood ,H.Lee,and R. Kastner , "MP core : Algorithm and Design Techniques for Efficient channel Estimation in wireless Application , "presented at design Automation conference (DAC) , Anaheim ,CA , 2005 .
[4] B.L. Hutchings and B.E.Nelson, "Gigaop DSP on FPGA, " Presented at acoustics, speech, and Signal Processing, 2001 . Preceeding .(ICASSP '01). 2001 IEEE International conference on, 2001.
[5] "Distributed arithmetic FIR filter v9.0, " Xilinx product Secification 2004.
[6] " FPGA Implementation of Subband Image Encoder using discrete wavelet transform" , by youn-Hong - Kim ,Kyoung-il jun, Kang Hyeon Rhee, 1991 IEEE TENCON.
[7] Practical FIR Filter Design in MATLAB R. Ricardo, A. Losada the Math Works, Inc.2004.
[8] Joseph B.Evans, "Efficient FIR Filter Architectures Suitable for FPGA Implementation" , IEEE Trans. Circuits & Systems , july 1994.
[9] J. Isoaho, J . Nousiainen and O. Vainio , "FPGA-Implementable Digital Filters" , More FPGAs. W .R. Moore and W.Luk, Abindon EE&CS books,1994.
[10] Joseph B. Evans , "Efficient FIR Filter Architecture suitable for FPGA Implementation " IEEE Trans on circuits and system-11 . Analog and Digital.
[11] Philip H.W. LEONG, "Trends in FPGA architecture and application " , IEEE computer Society, 2008 .
[12] J. Valls ,M. Peiro , T. Sansaloni, E. Boemo, "A study about FPGA based digital filters " , IEEE Workshop on Signal Processing Systems, 1998.

