ISSN (Online) : 2454-4159

International Journal of Advanced Research in Science Management and Technology

IJARSMT

Volume 2, Issue 3, March 2016

Different Optimization Techniques for Design of Low Pass FIR Filter

Chandrashekhar A. Kadam[1] ,Prof. Sameena Zafar[2]

PG Student, Dept. Of Electronics & telecommunication, PCST, Bhopal, M.P., India[1]

Professor, Dept. Of Electronics & telecommunication, PCST, Bhopal, M.P., India[2]

ABSTRACT — Digital filters are frequency selective system which is used to pass a certain range of frequency and to stop another range of frequency. The use of a filter plays an important part in a communication channel because it is effective at eliminating spectral leakage, reducing channel width, and eliminating interference from adjacent symbols (Inter Symbol Interference) ISI. They are actually characterized by their impulse responses. Depending upon the duration of the impulse response, digital filter are classified as Finite –Duration Impulse Response (FIR) and Infinite Duration Impulse Response (IIR) filters. Different techniques have been used for the design of FIR filter, which includes window based method frequency sampling method and various evolutionary algorithms are also being used for this purpose. The use of different optimization technique, such as Genetic Algorithm (G.A.), Particle Swarm Optimization (PSO) has been proved to be quite useful towards the design of these digital filters with certain specification. But using D.E. algorithm low pass FIR filter are also quite possible. D.E. Algorithm is better than other algorithms.

***INDEX TERMS* —** Digital filters, FIR filter, Differential Evolution, DE algorithm

1. INTRODUCTION

A filter is a frequency selective circuit that allows a certain frequency to pass while attenuating the others. These are mostly used in communication for noise reduction, video/audio signal enhancement etc. Digital filters are used in wide variety of applications from signal processing, aerospace, control systems, defense equipment's, telecommunications, system for audio and video processing to systems for medical applications to name just a few. Basically filter refers to a frequency selective device which extracts the useful portion of input signal lying within its operating frequency range and could be contaminated with random noise due to unavoidable circumstances. Analog filters are implemented with discrete components but the digital filters perform mathematical operations on a sampled, discrete time signal to reduce or enhance the desired features of the applied signal [1]. The use of different optimization technique, such as Genetic Algorithm (G.A.), Particle Swarm Optimization (PSO) has been proved to be quite useful towards the design of these digital filters with certain specification. Since the beginning of the nineteenth century, a significant evolution in optimization theory has been noticed. Genetic algorithm (GA), enunciated by John Holland in the year 1975, is one such popular algorithm which is based on the concept of "survival of the fittest" by Charles

ISSN (Online) : 2454-4159
International Journal of Advanced Research in Science Management and Technology
Volume 2, Issue 3, March 2016

Darwin [2]. Genetic Algorithm (GA) based design techniques are widely popular for synthesizing finite impulse response (FIR) filters. An effective design method for minimum phase digital FIR filters using GA has also been described in [3]. The algorithm Particle Swarm Optimization (PSO) was inspired by biological and sociological motivations and can take care of optimality on rough, discontinuous and multimodal surfaces. The aim of this optimization technique is to determine the best-suited solution to a problem under a given set of constraints. In mid 1990s, Eberhart and Kennedy enunciated an alternative solution to the complex non-linear optimization problem by emulating the collective behavior of bird flocks, particles and called their brainchild Particle Swarm Optimization (PSO) [4]. Kennedy and Eberhart introduced the concept of function-optimization by means of a particle swarm [5]. Suppose the global optimum of an *n*-dimensional function is to be located. The function may be mathematically represented as [6]: $f(x_1, x_2, x_3 \dots \dots \dots \dots \dots x_n) = f(\vec{X})$. Particle swarm optimization techniques can be used to design infinite impulse response (IIR) filter [7]. It is observed that the particle swarm algorithms are able to converge very rapidly when the error surface is relatively constant. This is the fundamental advantage of particle swarm algorithm for online adaptive filtering. By applying PSO to optimize transition sample values, the maximum stop band attenuation in FIR filter is obtained. It has been experimented that to design FIR filter, PSO is more superior to GA not only in the convergence speed but also in the performance of filter [8]. Differential Evolution (DE) [6] algorithm has been emerged as a very competitive form of evolutionary computing more than one decade ago. The first written article on DE appeared as a technical report by R. Storn and K. V. Price in 1995. Design of IIR filter using Differential Evolution (DE) algorithm for both magnitude response and group delay has been investigated in [9]. Design of an parameter IIR-filter using Differential Evolution has also been done in [10]. It has been studied in [11] that to design an acceptable filter, DE requires less iteration than GA for similar type of design. It has also been experimented that the convergence speed of DE is much better than GA too. For the design of higher order filter, as expected, the algorithms require more generations to design an acceptable filter. The performance of DE and GA has also been compared in terms of the computation time. It was seen that DE requires about 2–3 seconds although GA needs approximately 50 seconds to design an optimal IIR filter for 50 generations [11]. In terms of the final solution, the performance of DE is comparable to that of GA since the local search ability of DE is better than that of GA.

2. DIFFERENTIAL EVOLUTION

Differential Evolution (DE) algorithm has been emerged as a very competitive form of evolutionary computing more than one decade ago. This algorithm can optimize any function with D real parameters for any positive integer number D. At the beginning of the execution of the algorithm, size of the population should be selected. Population size (P) does not change during the minimization process. So, DE will utilize P number of D dimensional vector with each vector having the form shown as [6]: $x_{i,G} = [x_{1,i,G}; x_{2,i,G}; \dots \dots \dots . x_{D,i,G}]$, Where $i = 1,2,3 \dots \dots \dots \dots \dots . . P$ and G is the iteration number or generation number. Entire DE algorithms can be divided into four steps, namely Initialization, Mutation, Crossover or Recombination and Selection.

2.1 Initialization

This step indicates the start of this algorithm. Initially, the values of the parameter vector are chosen randomly in such a way that it should cover the entire parameter space. If distribution of the random variable is not mentioned, uniform probability distribution for random variables is generally assumed. Let $x_{i,j,1}$ denote the j^{th} element of the i^{th}member of population at first iteration. The values $x_{i,j,1}$ of must be within the upper and lower bound of the random variable and can be written as [10]: $x^L \leq x_{i,j,1} \leq x^U$.

2.2 Mutation

The step mutation actually expands the search space. To change the i^{th} member of the population$x_{i,G,}$ a mutant or donor vector $v_{i,G+1}$ is created in the process of mutation. Depending upon the generation of the donor vector from the parameter (or target) vector, different variants of DE has been developed in literature. For each parameter vector $x_{i,G}$; a mutant vector is generated using different equations in various schemes of DE. There are ten different mutation strategies depending upon the types of mutation and crossover to be performed. They are named as: DE/rand/1/exp [6], DE/rand/2/exp [6], DE/rand-to-best/1/exp [12], DE/best/1/exp [10], DE/best/2/exp [10], DE/rand/1/bin [6], DE/rand/2/bin [14], DE/rand-to-best/1/bin [10], DE/best/1/bin [13] and DE/best/2/bin [13]. In the DE/rand/1 [6] scheme the mutant vector of the next generation $v_{i,G+1}$ is generated according to the following equation [6] $V_{i,G+1} = x_{r_1,G} + F(x_{r_2,G} - x_{r_3,G})$, Where $i = 1,2,3 \ldots \ldots \ldots \ldots \ldots . . P$. The parameter "F" is called the Weighting Factor which is normally selected from the range [0, 2] and running index i is different from other three indicesr_1, r_2 and r_3 which are chosen from the set $\{1,2 \ldots . . . P\}$. As a matter of fact, DE scheme requires minimum 4 no of population for execution. DE/rand to best/1 follows the same procedure as that of DE/rand/1.

2.3 Recombination

Recombination incorporates successful solutions from the previous generation. It plays a significant role to increase the potential diversity of the population member. At the end of this step, the trial vector $u_{i,G+1}$ is developed from the elements of target vector $x_{i,G}$ and the elements of donor vector$v_{i,G+1}$. Elements of donor vector enter the trial vector with recombination probability (RP). The trial vector can be expressed as [12]: $u_{i,G+1} = [u_{1,i,G+1}; u_{2,i,G+1} \ldots \ldots \ldots . u_{D,I,G+1}]$,Where $i = 1,2,3 \ldots \ldots \ldots \ldots . . p$. Each member of the trial vector is formed in accordance with the following equation [15]: $u_{j,i,G+1} = \begin{cases} v_{j,i,G+1} \ if \ rand_{j,i} \leq RP \ or \ j - I_{rand} \\ x_{j,i,G} \ \ if \ rand_{j,i} > RP \ and \ j \neq I_{rand} \end{cases}$ In this equation, $rand_{j,i}$ is a random value in the range [0, 1] and I_{rand} is a random integer from [1, 2…….D]. RP denotes recombination probability and certainly is in the range [0, 1]. The above equation ensures that $u_{i,G+1}$ gets at least one parameter from$v_{i,G+1}$.

2.4 Selection

This is the final step of the evolutionary algorithm. Comparing the values of trial vector $u_{i,G}$ with the target vector $x_{i,G}$ it can be decided whether or not the trial vector will be able to be a member of the next generation. This can be represented mathematically as follows[15]: $x_{i,G+1} = \begin{cases} u_{i,G+1} \; if \; f(u_{i,G+1}) \leq f(x_{i,G}) \\ x_{i,G} \; if \; f(u_{i,G+1}) > f(x_{i,G}) \end{cases}$ If the trial vector $u_{i,G+1}$ yields smaller cost function than target vector $x_{i,G}$ then the value of trial vector is assigned to $x_{i,G+1}$, otherwise the old value of the target vector will be sustained. Mutation, recombination and selection process will continue until any termination criterion is reached. If after the execution of all the iteration still no termination criteria exists then the member of the population having the least functional value is chosen as the optimized solution to the concerned problem.

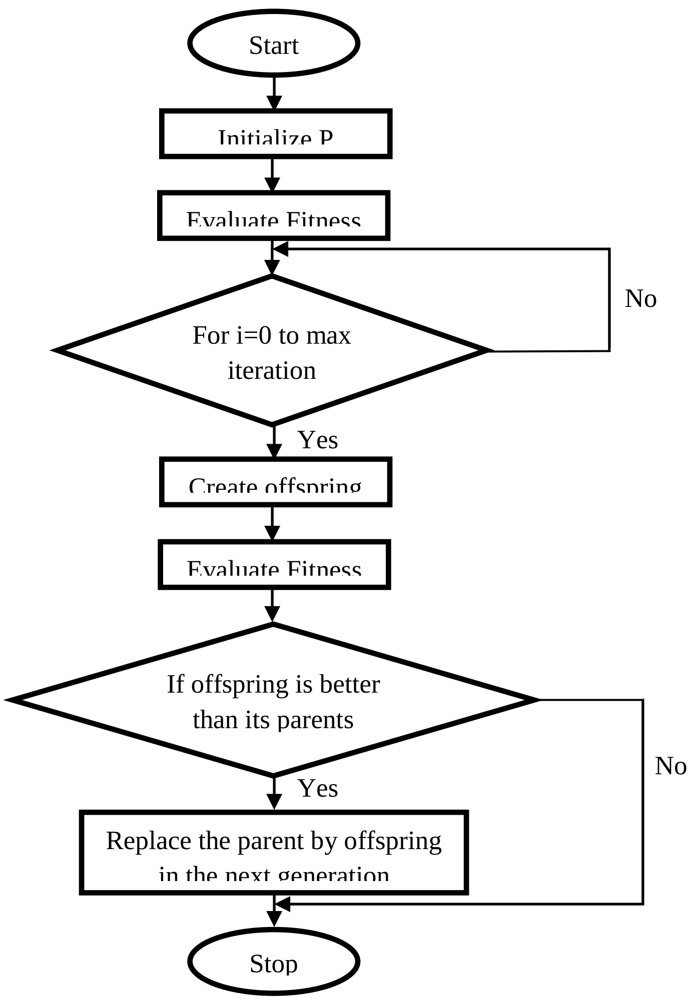

Fig 1: Flow diagram of differential evolution algorithm

III. CONCLUSION

Different optimization techniques have been used to design Low pass FIR filter but it has been seen that Differential Evolution (DE) algorithm is best than other algorithms. In the future this algorithm is better solution for designing of filters.

REFERENCES

[1] Ricardo A. Losada, "Digital Filters with MATLAB", *The MathWorks, Inc*., May 2008.

[2] S. S. Rao, "Engineering Optimization: Theory and Practice", *John Wiley & Sons, 4th edition*, 2009.

[3] W. Northcutt, "The Darwin Awards 3: survival of the fittest", *Plume*, 2004.

[4] J. Kennedy and R. Eberhart,"Particle Swarm Optimization", *In Proceedings of IEEE International Conference on Neural Networks*,pp.1942-1948, 2005.

[5] J. Kennedy, R. Eberhart and Shi Y, "Swarm Intelligence", *Los Altos*, CA.

[6] S. Das, A. Abraham and A. Konar , "Particle Swarm Optimization and Differential Evolution Algorithms: Technical analysis, Applications and Hybridization Prospects" *in Proceedings of Studies in Computational Intelligence (SCI) 116*, pp. 1-38, Springer-Verlag Berlin Heidelberg 2008.

[7] Wan-Ping Huang, Li-Fang Zhou, Ji-XinQian, "FIR Filter Design: Frequency Sampling Filters by Particle Swarm Optimization Algorithm", *In Proceedings of the Third International Conference on Machine Learning and Cybernetics*, Shanghai, August 26-29 ,2004.

[8] M. Najjarzadeh, A. Ayatollahi, "FIR Digital Filters Design: Particle Swarm Optimization Utilizing LMS and Minimax Strategies", 978-1-4244-3555-5/08, *IEEE*,2008.

[9] R. Storn, "Differential Evolution Design of an IIR-Filter with Requirements for Magnitude and Group Delay", *TR-95-026*, June 1995.

[10] R. Storn, "Differential Evolution Design of an IIR-Filter", *in Proceedings of Evolutionary Computation*, pp. 268-273, May 20-22, 1996.

[11] S. Das, P. N. Suganthan, "Differential Evolution: A Survey of the State-of-the-Art", *IEEE Transaction on Evolutionary Computation*. vol. 15. no.1, February 2011.

[12] A. Chandra, S. Chattopadhyay and S.K. Sanyal, "An Efficient Algorithm to Minimize the Number of Coefficients of an FIR Pulse-Shaping Filter", *in Proceedings of Annual IEEE India Conference (INDICON 2010)*, Kolkata, India, December 17-19, 2010.

[13] S. Chattopadhyay, S.K. Sanyal and A. Chandra, "Comparison of Various Mutation Schemes of Differential Evolution Algorithm for the Design of Low-pass FIR Filter", *in Proceedings of Second International Conference on Sustainable Energy and Intelligent System (SEISCON 2011)*, pp. 809-814,Chennai, Tamil Nadu, India, July 20-22, 2011.

[14] R.Storn, K. Price,"Differential Evolution-A Simple and Heuristic for Global Optimization over Continuous Spaces", *International Journal on Global Optimization*, pp. 341-359, 1997.

[15] S. Chattopadhyay, S.K.Sanyal and A. Chandra, "Design of FIR filter Using Differential Evolution Optimization & to study its Effect as a Pulse Shaping Filter in a QPSK modulated system", *IJCSNS International Journal of Computer Science and Network Security*,vol.10,no. 1, pp.313-321,January 2010.