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Design of IIR filters using hybrid optimization of Firefly and PSO Algorithm

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Abstract: In general, the physical systems are recursive and nonlinear in nature, this non-linear nature of the systems makes it challenging for optimization problems. Infinite impulse response (IIR) and non-linear filtersare used to realize real-world systems. As compared to FIR filters, IIR filters performs better for low order systems as it consists less no. of system parameters. Meta-heuristic optimization algorithms, which are basically nature-based algorithms are being used in solving optimization problems. A reconstructed version of Firefly algorithm (RFA) inspired for particle swarm optimization algorithm is presented. This RFA algorithm is population-based FA algorithm which creates a learning rule for the identification of the filter coefficients. RFA's performance is then compared to standard FA algorithm. The results shows that RFA is comparable to FA algorithm and standard IIR low pass and high pass filters.

Keywords:IIR filter, FIR Filter, PSO, Firefly algorithm, Optimization.

I. INTRODUCTION

Digital signal processing (DSP) has attracted much interest centuries owing to its broad range of apps in a wide range of single-dimensional (1-D) and multi-dimensional signal fields of engineering. Application areas involve biomedical signal processing, adaptive filtering, harmonic estimation, satellite image processing, and communication networks and Power of the system[1].

Digital filters are the single frequency components widely utilized in numerous signal processing apps due to their adaptability and simpler architecture. In relation, digital filters have a clearer transient response, stronger stopband attenuation as contrasted to analogue filters [2]. There are many apps like system identification, adaptive filtering, biomedical signal processing [3] and so on, in which digital IIR filter is commonly manipulated. All such approaches depend on improved workflow of IIR filter, which could be constructed either to use a standard approach or by computer-based technique. In this research paper, IIR filter technology relies on FA and PSO.

The paper is structured as follows: Section II show the design of IIR filter, Section III describes the particle swarm optimization, Section IV explain Firefly algorithm optimization, section V and VI show proposed objectives and results. Section VII demonstrates Conclusion.

II. IIR FILTER DESIGN FORMULATION

This article presents the proposed design for IIR filters. The input-output relationship is defined by the following difference equation:

$$Y(p) + \sum_{k=1}^{n} a_k\, y(p-k) = \sum_{k=0}^{n} b_k\, x(p-k) \quad (1)$$

here x(p) and y(p) are the filter's input and output, respectively andn $(n \geq m)$ is the filter's order. With the assumption of coefficient a_0= 1, the transfer function of the IIR filter is described as

$$H(z) = \frac{\sum_{k=0}^{m} b_k z^{-k}}{1+\sum_{k=1}^{n} a_k z^{-k}} \quad (2)$$

The commonly used approach to IIR filterdesign is to represent the problem as an optimization problemwith the mean square error (MSE). Generally, in genetic algorithms such as PSO, GSA, FA the fitness function is taken as the MSE as expressed in (3)

F(i)= $\frac{1}{Ns}$ [(d(i)-y(i))^2](3)

where Nsis the number of samples used for the computation ofthe error fitness function; d(i) and y(i) are the filter's desiredand actual responses, for every iterationsrespectively. The differenceis the error between the desired and the actual filter responses.

III. Particle Swarm Optimization (PSO)

PSO technique was designed by motivating from occurrences of communication behavior of birds, fish and insects, and effectively implemented in optimal design of digital filter [5] In Proposed method, the optimal model is defined by obeying an interesting aspect controlled by 2 factors: 'P_{best}' (local best component), which is the solution corresponding to current best solution of objective function and 'G_{best}' (global best component) which is the another solution corresponding to final best solution achieved in entire search. With first stage, initializing of population matrix of particles/swarm is conducted. Every other sequence of particle vector includes a potential answer of the specific issue. In second phase, this swarm matrix is modified using [6]:

$V_n(i+1)=wV_n(i) + c_1.r_1.[X_n(i) - P_{best\,n}(i)]+$
$c_2.r_2.[X_n(i) - G_{best}]$(4)

In above Eq. (4), V_n represents the velocity matrix, whose dimensionality is same as of the population/swarm matrix, wis the inertia weight that controls the search space by putting limit on particles, C1 and C2 are the cognitive and social scaling parameters; r1 and r2 is the random amount vector. The velocity associated with particles of swarm has to be in limit of certain range., now the population matrix is updated as :

$X_n(i+1)= X_n(i)+ V_n(i+1)$(5)

In the end, there is a greedy search method for figuring and revising P_{best} and G_{best}. PSO was developed in the CAD programme by obeying the pseudocode described in [7].

IV. Firefly Algorithm (FA)

Firefly is a nature-based algorithm inspired by the behavior of fireflies and their way of communication known as bioluminescent. It is proved in recent studies that this algorithm shows effective performance for discrete time problems.

By idealizing the bioluminescent characteristics of fireflies considering some idealized rules, the firefly algorithm was developed. These rules includes: 1) all fireflies are attracted to each other irrespective of their gender; 2) the degree of brightness of two fireflies is directly proportional to their attractiveness or vice versa; 3) objective function determines the degree of brightness of a firefly.

Th main tasks for the firefly algorithm are luminance of light or light intensity and determining the attractiveness. The attractiveness β is observed in the eyes of other fireflies around it. Hence for every other firefly, the brightness of a particular firefly will be different. The distance r_{mn}between firefly m and firefly n will vary. Now, the intensity of light will reduce as the distance between two fireflies decreases, the attractiveness β will also get affected by it. Hence we can form the attractiveness of a firefly in gaussian form as a function of Euclidian distance between two fireflies:

$\beta(r) = \beta_0 e^{-\gamma r^m}$(6)

Where r is the Euclidian distance between fireflies, β_0 is the degree of attractiveness at r=0, and γ is the constant light absorption coefficient. In experiment the value of γ is taken from 0.1 to 1. The distance r_{mn} between two firefly m and n at x_m and x_n respectively iscalculated by standard Euclidian distance as guven below:

$$r_{mn} = ||x_m - x_n|| = \sqrt{\sum_{i=1}^{d}(x_{m,i} - x_{n,i})^2} \quad (7)$$

Where $x_{m,i}$ is the $i'th$ component of the $m'th$firefly (x_m). Now, firefly m will attract to a firefly n that will be determined by the update equation given by:

$$x_m' = x_m + \beta_0 e^{-\gamma r^m}(x_n - x_m) + \alpha\varepsilon_m \quad (8)$$

Where, x_m' is the updated or new position, $x_m$is the old position, the second term of the equation is the attraction as discussed before and the last term is used for randomization, with α being the control parameter for randomization. ε_m is a gaussian or unform distributed random vector.

V. Proposed Firefly Algorithm

The conventional firefly algorithm works very efficiently. Every firefly works independently in firefly algorithm which makes it appropriate for parallel implementations. As the solutions reaches to its optima, its values are still changing. To improve it further, a damping coefficientα_0 is introduced which will be decreasing in every iteration as the solution approaches to its optima at a faster rate. Inspiring from PSO algorithm, in this hybrid algorithm, the position of the firefly will be updated using equation (8) and then velocity will be computed using equation (4) then again the position will be updated using equation (5). Updatae equation for this RFA is given below:

$$x_m' = x_m + \beta_0 e^{-\gamma r^m}(x_n - x_m) + \alpha\varepsilon_m + V_n \quad (9)$$

V_n represents the velocity matrix calculated from equation (4).

Steps for applying RFA :

1. Initialize random population of P fireflies. The coefficients of filter are to be chosen from this population P. Every firefly will consist of k parameters and one parameter corresponds to one coefficient of the filter.
2. Next step is to define algorithm parameters such as γ, m and β_0 for FA and RFA, C1,C2, for PSO.
3. Set the number of iteration N. For the input $\{x_m\}_{m=1}^{N}$, the output will be Y=$[y(1)\, y(2) \ldots y(N)]^T$. Add gaussian noise then the outcome will be considered as the desired signal.
4. The next step is to calculate fitness for the algorithms for which we have used MSE as fitness function. Desired output is compared to the current $i'th$firefly by using:

   MSE(i) = $\frac{1}{N}[(Y - Y'_k)^T(Y - Y')]$ (10)
5. For PSO algorithm, equation (4) and (5) will be used to update each particle.
6. For FA algorithm, equation (8) will be used to update each firefly's movement.
7. For RFA algorithm, equation (9) and (4) will be used to update each firefly's movement.
8. For every iteration, obtain the MSE based fitness given in equation (10).
9. This process will terminate after reaching the maximum number of iterations or at predefined MSE level.

VI. SIMULATION RESULTS

The simulation part of this work is done on MATLAB a signal sin(t) is taken as input then added gaussian noise, now a 6th order filter is designed and then passed though filters with the coefficients of FA and RFA for comprehensive comparison. Algorithm parameters chosen for this simulation of FA; $\beta_0 = 1$, m=2 and $\gamma = 1$. For RFA;$\beta_0 = 1$, m=2,$\gamma = 1$, C1,C2=2, damping ration=0.9, weight=0.2, V_{max} =1, V_{min}=0.1, population size=100, no. of iterations=200.

Fig1. shows the fitness comparison between conventional FA and reconstructed FA (RFA) the for 200 iterations performance of RFA is comparable to FA.

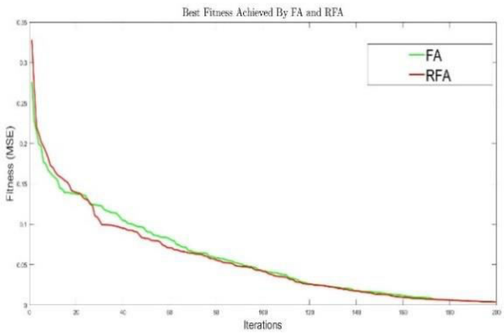

Fig. 1. Fitness comparison between FA and RFA.

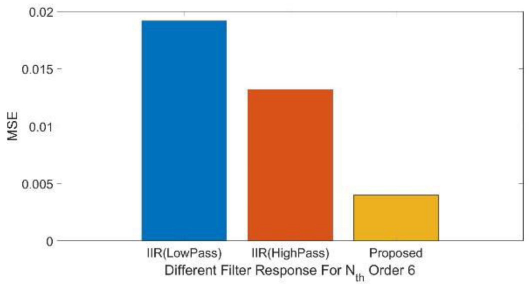

Fig. 2. MSE comparison for IIR low pass, IIR high pass and proposed RFA.

In fig 2., MSE of standard 6^{th} order low pass IIR filter, high pass IIR filter and RFA is compared. RFA clearly performs better that standard IIR filters.

VII. CONCLUSION

In this article, a newly invented optimization method inspired from FA and PSO are utilize for constructing IIR filter where FA due to interactions of masses and directed by the velocity has been implemented to the optimal creating of 6th order low pass, high pass, IIR digital filter. The optimal filters acquired comply with the fitness analysis and bring the comparable fairly good results. PSO is an optimized, steady, population-based stochastic search method with the interesting characteristics of a strategy and the possibilities to collide quickly to a significantly larger plan. Besides that, except for conventional optimization method, it has the ability to integrate a wider search space and a non-differentiated fitness function. FA and PSO merge very quickly to the optimum process of the highest quality and attain the lowest possible error fitness value at a slightly lower processing time. Statistically enhanced FA outcomes also validate the effectiveness of the suggested method for the introduction of digital IIR filters.

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