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An Efficient Hybrid SIMBO-GA Approach to Design FIR Low Pass Filter

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Abstract
In this paper a narrative approach for designing FIR low pass filter is presented by practicing hybrid technique of Swine Influenza Model based Optimization (SIMBO) and Genetic Algorithm (GA). Premature convergence was the major difficulty faced by SIMBO algorithm individually in FIR filter design. To address this problem, a hybrid SIMBO-GA is proposed in this paper. GA is used to help SIMBO escape from local optima and prevent premature convergence. Results are presented and compared in term of magnitude response with Differential Evolution Particle Swarm Optimization (DEPSO), Genetic Lbest Particle Swarm Optimization with Dynamically Varying Neighbourhood (GLPSO DVN). A comparison of simulation results divulges that SIMBO-GA seems to be promising tool for FIR filter design.

Keywords: FIR Filter, SIMBO-GA, DEPSO, LPSO, GLPSO DVN.

1. Introduction

Conventionally, different techniques exist for the design of digital filters. The simplest design of FIR (finite impulse response) filter is achieved using window method. In this method, ideal impulse response is multiplied with a window function (T. W. Parks & C. S. Burrus 1987). The various available windows limit the infinite length impulse response of ideal filter into finite window to design an actual response. But windowing methods do not allow sufficient control of frequency response in the various frequency bands and other filter parameters such as transition width (J. I. Ababneh & M. H. Bataineh 2008). Furthermore, the windowing method does not permit individual control over approximate error in various bands. So, better filter result from minimization of maximum error in both stop band and pass band of the filter which leads to equiripple filters (Vasundhra et al. 2013). Such filters can be achieved using evolutionary methods. Since population based stochastic search methods have proven to be effective in multidimensional nonlinear environment.

Many of stochastic search methods such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Differential Evolution (DE) algorithms and many more such algorithms have been used by different authors to implement digital filters design. One of such optimum FIR digital filter using computational intelligence based optimization algorithm has been described in (F. Teixria & A. Romariz 2007). Design of Low-pass filters with variants of PSO has been described in (S. Mandal et al. 2011). Efficient and accurate optimal linear phase FIR filter design using opposition-based Harmony Search algorithm has been described in (S. K. Saha & R. Dutta 2013). Also Differential Evolution Particle Swarm Optimization (DEPSO) for digital filter is described in (B. Luitel, & G. K. Venayagamoorthy 2008). In this paper, SIMBO and GA have been used for the design of linear phase FIR filters.

2. Digital Filter Design

In FIR the response of FIR filters decay with increase in time. The output depends upon the present and previous inputs. It is non recursive filter characterized by equation:-(E. C. Ifeachor & B. W. Jervis 2001)

$$y(n) = \sum_{k=0}^{N-1} h(k)\, x(n-k) \qquad (1)$$

where h(k) are the impulse response coefficients of the filter, n is the filter length, y(n) is the output at discrete time instance n and x(n-k) is the filter input delayed by k samples.

Various filter parameters come into picture are pass band and stop band edge frequencies ($\omega_{p,}\ \omega_s$), the pass band and stop band ripples, stop band attenuation and transition width. Significance of the parameters in the actual filter with respect to ideal filter is depicted in Fig.1 as described in (E. C. Ifeachor & B. W. Jervis 2001).

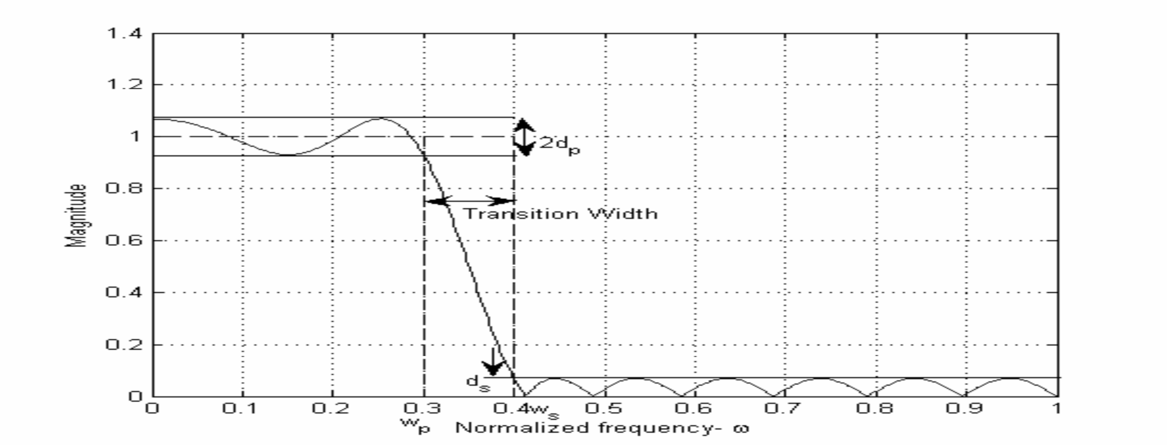

Figure 1. Ideal and Actual Filter Magnitude Response

3. Proposed SIMBO-GA Algorithm

3.1 SIMBO Algorithm

The SIMBO that has been described in (S. S. Pattnaik et al. 2013) mimicked from Susceptible-Infectious-Recovered (SIR) model as described in (W. O. Kermac & A. G. McKendrik 1927). The model of SIMBO is presented in Fig. 2.

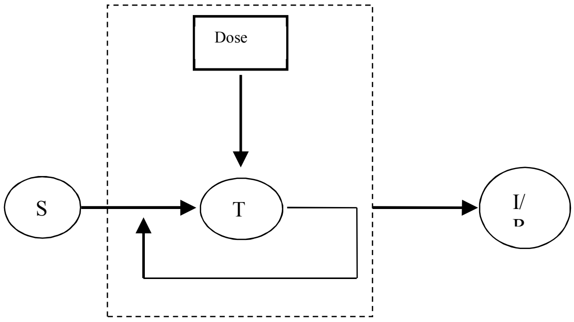

Figure 2. Model of SIMBO

SIMBO performs the optimization through treatment based on probability. In this model everyone is assumed to be susceptible because one infected individual in population lead to the total population susceptible. The treatment is given to all suspected cases in the population by varying amount of antiviral drugs depending upon current health. The percentage of antiviral drugs is dependent on primary and secondary symptoms characterized by equation (3) as follows and current health and pandemic health as given in (D. G. Jadhav et al. 2014).

$$Primary(Day) = (Fe * Co * Fathead * NV * Dai) * \exp\left(-\frac{TD}{Day}\right) \tag{3}$$

where Fe denotes fever, Co denotes cough, fathead denotes fatigue and headache, NV denotes nausea and diarrhoea. The secondary symptoms caused per day is represented in mathematical expression (D. G. Jadhav et al. 2014) as given below in equation (4)

$$RO(Day) = 1 - \exp(Primary(Day)) \tag{4}$$

where RO is the secondary symptoms per day. The dose given to the individual and due to dose the change in individua state is given as equation (5) and (6)

$$Dose(m+1) = Dose(m) * Md + Primary(Day) * rand * \left(1 - \frac{Current\_health(m)}{rand} * PH\right) + RO(Day) * rand * (Curren\_health(m) - PH) \tag{5}$$

$$S(m+1) = S(m) * Ms + Dose(m+1) \tag{6}$$

where Md and Ms are the non-linear momentum factors, these restrict the individual’s treatment and state inside the defined limits without checking the health every day. As health of individual deteriorates, dose of the drug increases or additional dose is added. PH is pandemic health that correspond to best fitness value which further correspond to best pandemic state i.e. PS, that provides optimized coefficients for digital filter The SIMBO performs optimization through two basic steps as follows

A. Evaluate Health: The individuals before they undergo treatment process are diagnosed by calculating health of individual depending upon the fitness function.

B. Treatment: Treatment is trial and error process of any particular disease, physician starts treatment with some

initial high dose and waits to observe the response of the patient, and hence amount of dose for further treatment depends upon the current health.
The pseudo code of SIMBO is given in Figure 3.

```
        Initialization of parameters
                TI, TD, Fe, Co, fathead, NV, Dai, α, PS, PH, Md and MS
for Day= 1:TD
    for i= 1:TI
    current_health(i)= Evaluate Fitness Function (S(i))
    end
    Update PH and PS
end
Primary (Day)= (Fe*Co*fathead*NV*Dai)*exp(-TD/Day)
RO (Day)= 1-exp(-Primary(Day))
Treatment (T)
for m=1:TI
     if rand>α
Dose(m+1)= Dose(m)*Md+Primary(Day)*rand*(1-Current_health
         (m)/ rand*PH)+RO(Day)*rand*(current_health(m)-PH)
S(m+1)=S(m)*Ms+Dose(m+1)
     end
end
```

Figure 3: Pseudo Code of SIMBO

The total number of days for which individual undergoes treatment process and initial dose to all the individuals in population as physician starts treatment with standard dose that needs to be specified.

3.2 Genetic Algorithm (GA)

GA is mainly a probabilistic search technique, based on the principles of natural selection and evolution. At each generation it maintains a population of individuals where each individual is a coded form of a possible solution of the problem at hand called chromosome (S. Mukherjee et al. 2011). Chromosomes are constructed over some particular alphabets, e.g., the binary alphabet {0, 1}, so that chromosomes values are uniquely mapped onto the real decision variable domain. Each chromosome is evaluated by a fitness function or the objective function of the corresponding optimization problem.
Steps of GA as implemented for the optimization of coefficients are (S. Mandal et al. 2011):
A. Initialization of real chromosome string of n_p population, each consisting of set of coefficients. Size of the set depends on the number of coefficients in particular filter design.
B. Decoding of strings and evaluation of error of each string.
C. Selection of noble strings in order of increasing Error values from the minimum value.
D. Copying of the noble strings over the non-selected strings.
E. Crossover and mutation to generate off-springs.
F. Genetic cycle updating.
G. The iteration stops when the maximum number of cycle is reached. The grand minimum Error and its corresponding chromosome string is finally obtained.

3.3 Steps for Hybridization

After the completion of treatment process of SIMBO algorithm, final set of states of the individuals immune to swine flu are passed as the initial states for population in GA. The further steps for hybridization are as follows:
A. Implementation of SIMBO in MATLAB.
B. Design of FIR low pass filter using SIMBO.
C. The final states of the individuals in the population are considered to be initial population of GA.
D. Fitness function is same as used in SIMBO algorithm.
E. The order of filter is kept same with same specifications.
F. The GA is run for different iterations with different stopping criteria in order to achieve best possible results.

4. SIMBO Based Digital Filter Design

The filters are designed to optimize the coefficients which give the best frequency response. The individual in the population are distributed in N dimensional search space, where N is the filter length. On each day, current health of individuals are used to calculate new coefficients i.e. best PS amongst all the individuals that represent new set of coefficients used to design desired digital filter. An error function to approximate error used in Parks-McClellan algorithm for filter design is given below (S. K. Saha et al. 2013)

$$\mathrm{E}(\omega) = G(\omega)[H_d(e^{j\omega}) - H(e^{j\omega})] \quad (7)$$

Where G (ω) is the weighting function used to provide different weights for approximate errors in different frequency bands, $H_d(e^{j\omega})$ is the frequency response of the desired filter and $H(e^{j\omega})$ is the frequency response of approximate filter. The Fitness function of (B. Luitel & G. K. Venayagamoorthy 2008) used as objective function of the proposed hybrid algorithm and is shown in equation (8)

$$\mathrm{J} = 1/\mathrm{N_f} \sum_{\mathrm{k}=1}^{\mathrm{N_f}} (\mathrm{ideal}(\mathrm{k}) - \mathrm{Actual}(\mathrm{k}))^2 \quad (8)$$

This is called mean squared error where ideal (k) and actual (k) are the magnitude response of the ideal and the actual filter. The algorithm tries to minimize this error and thus increase the fitness.

5. Results and Discussion

5.1 Analysis of Magnitude response of FIR low pas filters.

In this paper filter specifications considered are as follows: pass band ripples δ_p=0.1 i.e. $A_p = 0.915$ dB and stop band ripples δ_s =0.01 i.e. $A_s = 40$ dB. The pass band cutoff frequency ω_p is 0.25 and stop band cutoff frequency ω_s is 0.30 respectively (B. Luitel et al. 2008). The sampling frequency has been chosen as f_s=1Hz. The number of sampling points is taken as 256. Filter with 20 coefficients i.e. 19 order is designed. Filter was designed for 100 individuals in the population and 1000 iterations are used. An initial standard dose for all the individuals is considered to be 0.92. Table 1 represents control parameters of SIMBO, SIMBO-GA.

Table 1: Control Parameters of SIMBO, SIMBO-GA

SIMBO	SIMBO-GA
Population Size= 100, Iterations= 200, Fe= 0.4, Co= 0.4, fathead= 0.2, NV= 0.2, Dai= 0.2, α= 0.2 and initial Dose=0.9	Population size=100, Iterations= 1000, mutation rate=0.01 and crossover rate=1

Algorithms are run for several times and best results obtained using SIMBO and SIMBO-GA are discussed below.

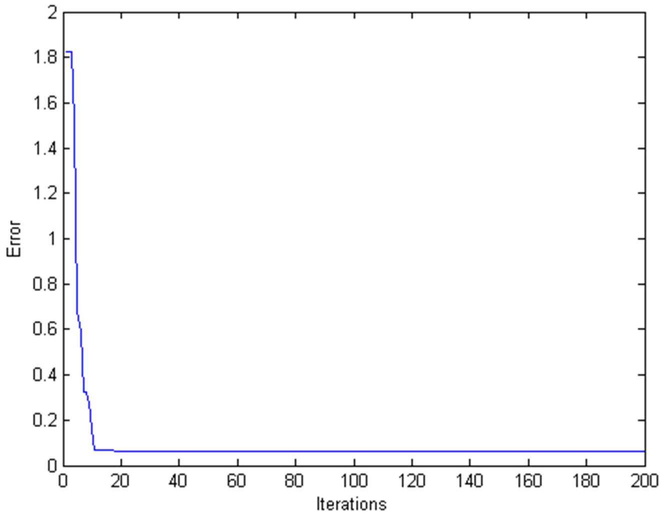

Figure 4: Error Graph for SIMBO

The problem with SIMBO algorithm was trapping around local minima leading to the premature convergence. In order to overcome the problem of premature convergence, hybrid SIMBO-GA algorithm was designed for which error plot has been shown in Figure 5 as

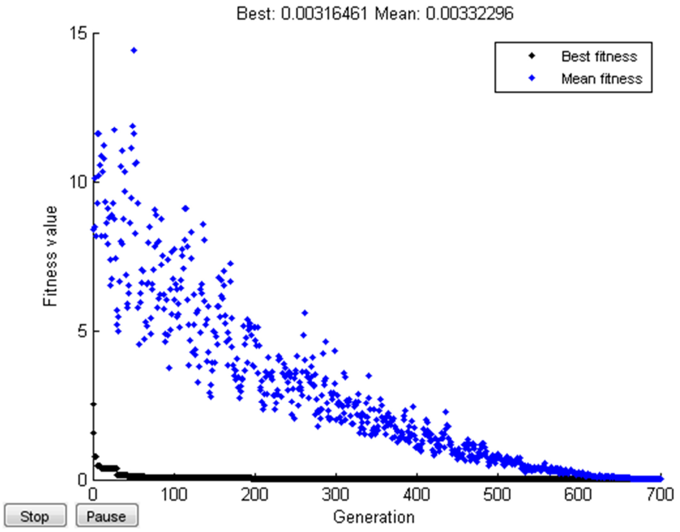

Figure 5: Error Graph for SIMBO-GA

SIMBO-GA helps to achieve best coefficients and overcome the problems faced by SIMBO algorithm individually resulting in optimum filter as shown in Figure 6 and Figure 7. Table 2 represents comparison of pass band ripples and maximum stop band attenuation in dB obtained using SIMBO and SIMBO-GA.

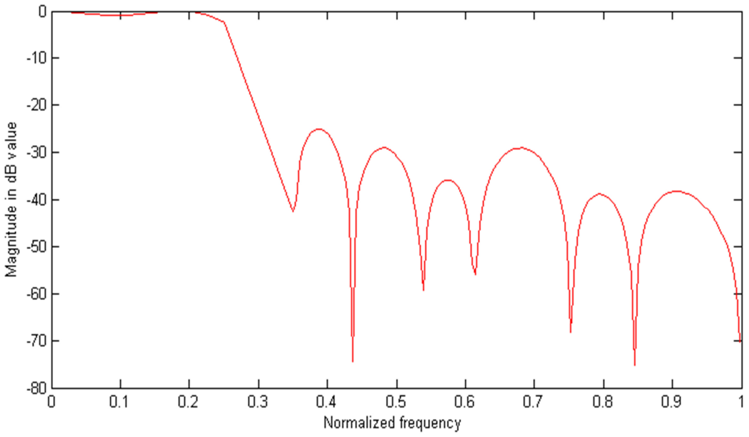

Figure 6: Plot for the Low Pass Filter using SIMBO

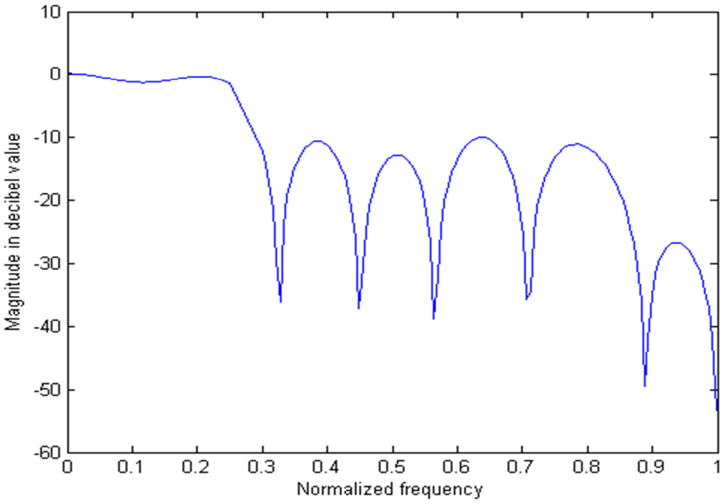

Figure 7: Plot for the Low Pass Filter using SIMBO-GA

Table 2: Comparison of Stop Band Attenuation and Pass Band Ripples using SIMBO, SIMBO-GA

Algorithm	Pass band ripples(dB)	Stop band attenuation(dB)	Transition width
SIMBO	0.99	-09.97	0.05
SIMBO-GA	0.91	-25.05	0.1

Table 2 depicts the maximum stop band attenuation is achieved obtained using SIMBO-GA as well as near to the desired value as mentioned above, but stop band attenuation obtained using SIMBO was very far from achieving the desired results. Also pass band ripples in dB obtained using SIMBO-GA are approximately same as desired, but those obtained using SIMBO are away in order to design optimum filter.

5.2. Comparative Analysis of Magnitude response of Published Results

In order to compare the algorithms in terms of pass band ripples in dB and maximum stop band attenuation figure 8 shows plot of low pass filter using SIMBO-GA, DEPSO, GLPSO DVN. Table 3 shows summary of SIMBO-GA results with aforementioned algorithms.

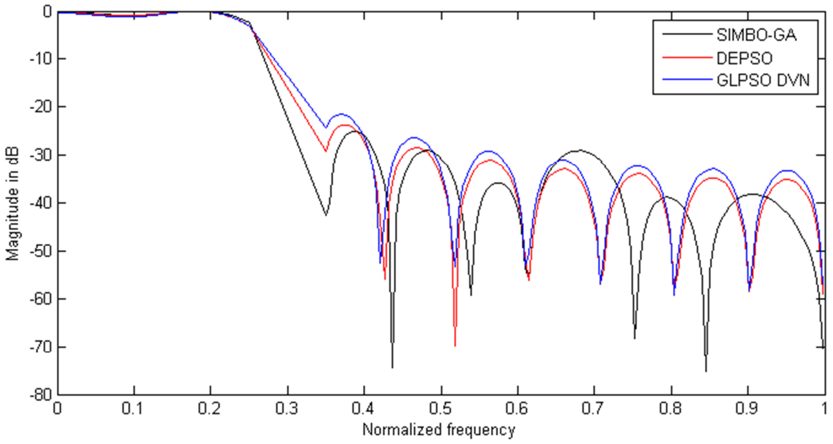

Figure 8: Plot of low pass FIR filter using afore mentioned algorithms

Table 3: Summary of SIMBO-GA Results with other Algorithms for Low Pass Filter

Algorithm	Pass band ripples(dB)	Stop band attenuation(dB)	Transition Width
SIMBO	0.99	-09.97	0.05
SIMBO-GA	0.95	-25.05	0.1
DEPSO (B. Luitel et al. 2008)	0.94	-23.72	0.1
GLPSO	1.2	-21.62	0.1

From the figure 7 and Table 3, it is apparent that the proposed filter design advance towards SIMBO-GA produces higher stop band attenuation with -25.05 dB and smaller pass band ripples 0.95 dB as compared to aforementioned algorithms. Table 4 shows optimized coefficients of FIR low pass filter using SIMBO and SIMBO-GA.

Table 4: Optimized Coefficients of FIR Low Pass Filter

Coefficients	SIMBO-GA	SIMBO
h(1)=h(20)	0.0174	-0.0140
h(2)=h(19)	0.0326	0.0391
h(3)=h(18)	0.0123	0.0862
h(4)=h(17)	-0.0179	-0.0603
h(5)=h(16)	-0.0505	-0.0519
h(6)=h(15)	-0.0510	-0.0143
h(7)=h(14)	0.0033	-0.0144
h(8)=h(13)	0.0996	0.1034
h(9)=h(12)	0.2000	0.1484
h(10)=h(11)	0.2734	0.1885

6. Conclusion

This paper presents novel and accurate hybrid optimization techniques that involve the best practices of both algorithms that help to save the individuals from being trapped in local minima, thus guiding them towards the global solution. Simulation results depicted that proposed algorithm outperforms DEPSO, LPSO, LGPSO DVN in the accuracy of magnitude response of speed.

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