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SYNERGY OF BACTERIAL FORAGING AND PARTICLE SWARM ALGORITHM FOR LOW PASS FILTER DESIGN

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Abstract

Social foraging behavior of Escherichia Coli bacteria has been analyzed to develop an algorithm to solve optimization problem in Electronics and Control Industry. The chemotactic movement of a virtual bacterium models a solution of optimization problems. Designing of FIR filter is multimodal optimization problem. This paper presents a design of linear phase digital low pass filter using bacterial foraging with particle swarm optimization. Optimization is the process used for minimized or optimized the conflicts present in design of any filter. For realization of any filter design algorithm it's generate a set of coefficients. These coefficients are used to provide ideal frequency response characteristics. In this paper realization of FIR digital filter for different algorithm is performed. The comparison shows that BFO-PSO algorithm provides high accuracy, better convergence speed, robustness, scalability and best solution quality as compare to conventional BFO algorithms.

Keywords: PSO (Particle Swarm Optimization), BFO (Bacterial Foraging Optimization), EColi (Escherichia Coli), FIR (Finite Impulse Response), IIR (Infinite Impulse Response).

Introduction

With the evolution of new technologies, intensive research made in Digital signal Processing (DSP) have had great importance in Electronics and Communication Engineering. Digital filters are basic building blocks in various DSP applications. Various optimization techniques like Real Code Generation algorithm (RGA), Swarm Intelligence Technique (SI), Bacterial Foraging and Tabu Search Optimization (BFTS), Evolutionary Programming (EP), Evolutionary Strategies (ES), Ant Colony Optimization (ACO), Opposition based Harmony Search (OHS) etc are used to find best optimal solution. In 2001, Prof. K. M. Passnio proposed an optimization technique known as Bacterial Foraging Optimization (BFO) based on social foraging behavior of E Coli bacterium cell [1]. Until date there have been many successful application of BFO algorithm in optimal control industry, harmonic estimation, transmission loss reduction and so on. PSO is a evolutionary optimization technique developed by Dr. Russel Eberhart & Dr. James Kennedy [2] in 1995 desired by group behavior of bird flocking and fish schooling. Every bacterium tried to maximize energy obtained per unit time during its foraging process. The

selection behavior of bacteria tends to eliminate poor foraging strategies and selection of improved foraging strategies. Many attempts have been using PSO algorithm for design of digital filter [3].

A digital filter is a selective network that performs mathematical operation on a digital input using some digitized hardware and software, digital output is produced. On the other hand, analog filter perform action on an analog input using analogue hardware and software networks. Analog filter operates on a continuous time analog signals. Digital filters are used more comparatively with analog filters because 1) digital filter has less ripples than analog filter in pass band 2) digital filter have better signal to noise ratio 3) provides better stability and 4) better accuracy. Digital filter are more expensive than analog filters due to increased complexity but they make practical many designs. Analog filter are cheap and provides large dynamic rang in both amplitude and frequency. In analog filters limitations are imposed by electronics components such as resistors and capacitors whereas no such limitations in digital filters. One can achieve complex and selective designs due to definite nature of filter coefficients. Digital filter provides lower pass band ripple, higher stop band attenuation and faster transition rate. Thus

performance of digital filter is better than analog filter in many aspects. A simplified block diagram of digital

filter with analog input and analog output is shown in figure 1.

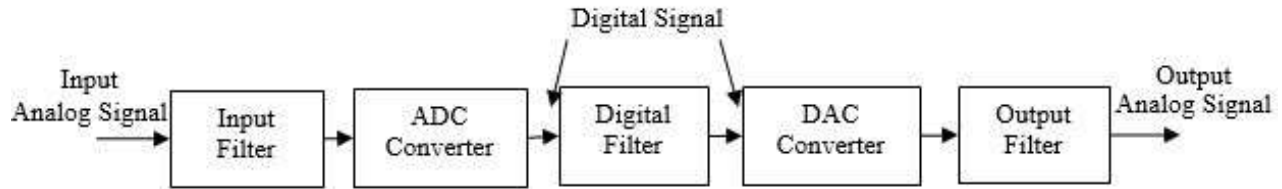


Figure 1: Block diagram of digital filter.

Digital filters are classified as FIR Finite Impulse Response and IIR Infinite Impulse Response depends upon nature of impulse function [4]. FIR filters have finite impulse response since the impulse response settles to zero within a finite amount of time whereas IIR filter have infinite impulse response since the impulse response is non zero over infinite amount of time. FIR filter provides attractive choice in design and stability. By designing filter taps to be symmetrical about center tap, FIR filter have exact linear phase and needs to provide only half of filter coefficients. The main desirable features of FIR filter are having exact linear phase characteristics at all frequencies, high filter order and stability. On the other hand, IIR filter have non linear phase characteristics and low filter order. Implementation of FIR filter is easier due to no feedback is required so that impulse response will be finite [5]. FIR filter have only zeros (no pole), all the poles all located either at origin or within the unit circle also known as non-zero filters. Output of digital filter is only depends on the input at that time but in analog filters output is depends on both input and previous output. FIR delay characteristics are much better than IIR but they require more memory. In IIR filter delay and distortion adjustments can alter the poles and zeros makes filters to become to difficult and unstable whereas FIR always remains stable. If we analyzed the input signal before filtering than it is easy to decide type of filter is to be used. FIR filter used where linear phase time domain characteristics matters [6]. Otherwise when only frequency response is considered, IIR digital filters are used which have low order, less complexity and easier to design.

are concatenated to form other half due to symmetrical nature of FIR filter.

The frequency response of FIR filter is calculated as:

$$H(w_k) = \sum_{n=0}^N h(n)e^{-jwn} \quad (3)$$

$$w_k = 2\pi k/N$$

$H(w_k)$ is Fourier Transform of $h(n)$. The particles i.e. coefficients vector $[h_0, h_1, \dots, h_n]$ which is optimized is represented in $(N+1)$ dimension space. The frequency is sampled with N points.

$$H_d(w) = [H_d(w_1), H_d(w_2), H_d(w_3), \dots, H_d(w_N)]^T \quad (4)$$

Filter Design: The main advantage of FIR filter is that they can achieve exactly linear phase frequency response. Since the phase response of filter is known, the design procedures are reduced to real valued approximation problems where coefficients have to be optimized with respect to magnitude response only. Impulse response of a digital filter is given as [5][7]:
 $H(Z) = \sum_{n=0}^N h(n) Z^{-n} \quad n = 0, 1, \dots, N \quad (1)$
 $H(Z) = h(0) + h(1) Z^{-1} + \dots + h(N) Z^{-N} \quad (2)$
 $h(n)$ is impulse response of the filter. N is order of filter. Filter has $N+1$ numbers of filter response coefficients. The value of $h(n)$ determine the type of filter i.e. low pass, high pass, pass band and stop band filter. The value of impulse response $h(n)$ are to be determine using optimized algorithms. In this paper combined approach of bacterial foraging and particle swarm algorithm used for optimal design of low pass filter by finding the filter coefficients. For design of filter, general specification of filter design like pass band, stop band attenuation, order of filter, sampling frequency and transition frequency have been considered. In BFO-PSO algorithm particles or bacteria represents $h(n)$ elements. These particles/bacteria are updated after each iteration level. Error fitness value or cost value function is calculated using new coefficients. A specified level of cost function is taken; iteration is continuous till the maximum iteration level is reached. The main advantage of design of linear phase filter is symmetry about centre tap due to which coefficients are also symmetrical and only half of the coefficients are needed to update by any type of algorithm and they

$$H_i(w) = [H_i(w_1), H_i(w_2), H_i(w_3), \dots, H_i(w_N)]^T \quad (5)$$

Where $H_d(\omega)$ represents magnitude response of designed filter and $H_i(\omega)$ represents magnitude of ideal filter. Ideal response of low pass filter is given as:

$$H_i(\omega) = \begin{cases} 1 & \text{for } 0 \leq \omega \leq \omega_c \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

ω_c is cut-off frequency of low pass filter.

An ideal filter has magnitude of one in pass band and zero magnitude in stop band given in (6). In any optimization algorithm, error fitness function plays an important role. Different error functions are used depends on type of evolutionary technique. Proper choice of error function is very important for successful working of any evolutionary optimization method. An error function given in (7) is the approximate error function given by Parks and McClellan (PM) [8] in which N , ω_p , ω_s and ratio of δ_p/δ_s are fixed.

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

Where $H_d(e^{j\omega})$ is the frequency response of designed filter and $H_i(e^{j\omega})$ is the frequency response of ideal filter. $G(\omega)$ is the weighting function used to provide different weight for errors in filters. Major drawback of this algorithm is the fixed value of δ_p/δ_s . Other different kind of error fitness function used in different evolutionary technique given in (8) and (9) given by (Karaboga and Cetinkeyal, 2006; Najjarzadeh and Ayatollahi, 2008; Luitel and Venayagamoorthy, 2008).

$$\text{Error} = \max \left\{ \sum_{i=1}^N [|| H_d(e^{j\omega}) - |H_i(e^{j\omega})||] \right\} \quad (8)$$

$$\text{Error} = \max \left\{ \sum_{i=1}^N [|| H_d(e^{j\omega}) - |H_i(e^{j\omega})||]^2 \right\}^{1/2} \quad (9)$$

In this paper, an error function given in (10) has been considered as fitness function is used to improve flexibility in error function is to be minimized, so that the desired levels of δ_p and δ_s may be individually specified given by (Ababneh and Bataineh, 2008;

Sarangi et al., 2010; Mandal et al., 2011) [9]. Error fitness functions to be minimized using this evolutionary algorithm.

$$J_1 = \max (|E(\omega)| - \delta_p) + \max (|E(\omega)| - \delta_s) \quad (10)$$

Where ω_p and ω_s are pass band and stop band cutoff frequencies respectively and δ_p and δ_s are pass band and stop band ripples respectively. For a linear phase symmetric filter, only half of the filter coefficients need to be calculated, the dimension of problem is halved. This reduced the computational burden of the algorithm for design of linear phase even symmetrical FIR filters. In order to achieve higher stop band attenuation and to have better control on the transition width, an error function given in (11) is used. This proposed algorithm has considerable improvement over other optimization techniques.

$$J_2 = \sum abs [abs (|H(\omega)| - 1) - \delta_p] + \sum abs [abs (|H(\omega)|) - \delta_s] \quad (11)$$

First term of (11), represents $\omega \in$ pass band including a portion of transition band and second term represents stop band including the rest portion of transition band. Choice of transition band depends on pass band and stop band edge frequencies. Each algorithm tries to minimize the error fitness function and optimize the filter performance.

Bacterial foraging with particle swarm optimization

The social foraging behavior of E. Coli bacteria [10] and implicit parallelism behavior of swarm of birds or collective intelligence [11] of a group with limited capability is used to solve non linear optimization problem in designing of digital filters. This classical combined algorithm has great importance in solving real world optimization problems as shown in figure 2.

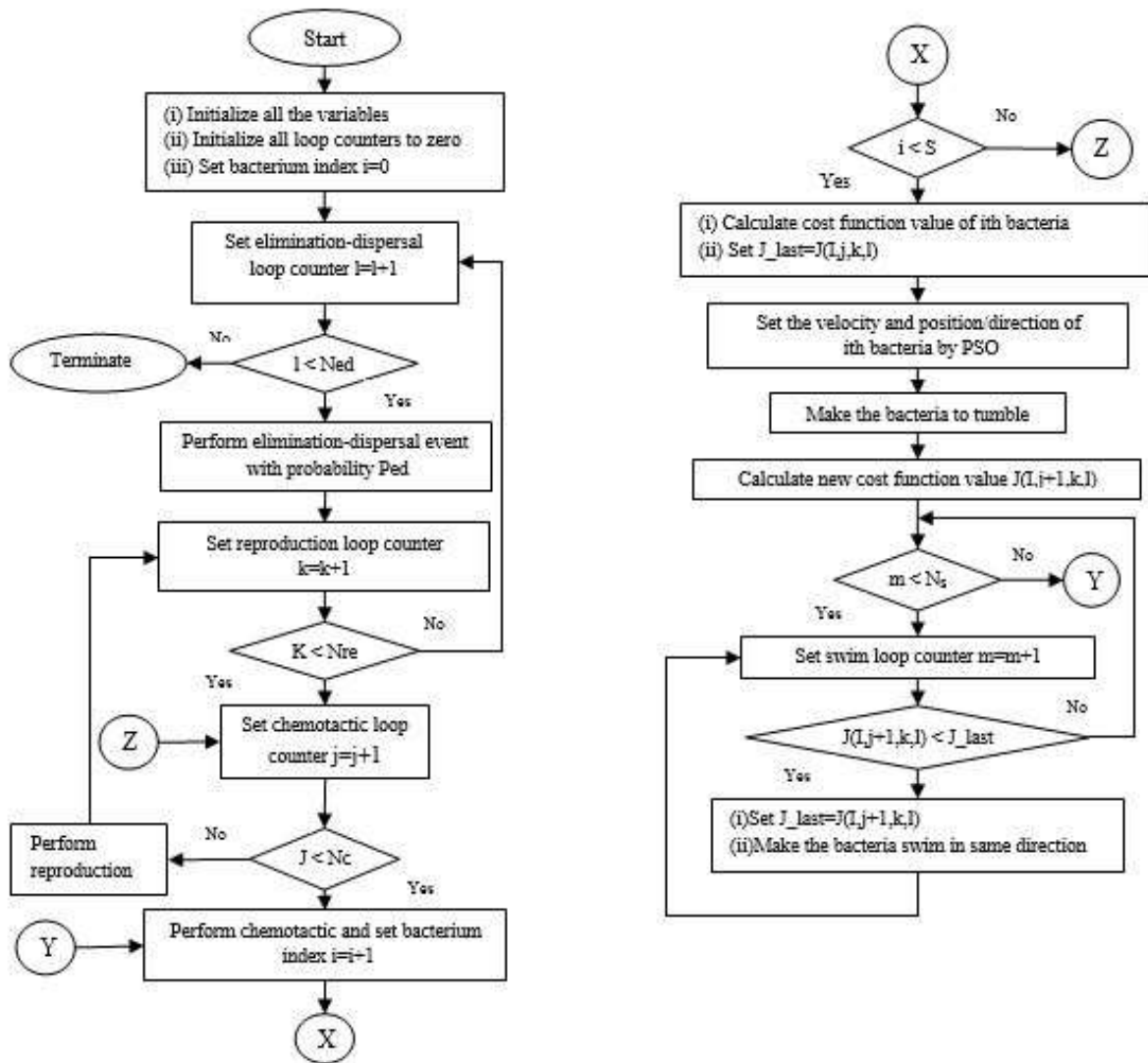


Figure 2: Flow chart of BFO-PSO

Bacterial foraging optimization

Bacterial foraging is a population based optimization technique developed by Prof. K. M. Passino in 2001[1], inspired by social foraging behavior of *Escherichia Coli* which is used to solve optimization problems of filters. BFO algorithm based on foraging strategies (method of finding, handling and taking) of *E Coli* bacterium cells that tend to eliminate poor foraging strategies. BFO formulate the foraging behavior exhibit by bacteria such that it maximizes their energy intake per unit time.

It consists of mainly four steps are such that it maximizes their energy intake per unit time. It consists of mainly four steps are chemotactic, swarming, reproduction and elimination/dispersal respectively.

Natural selection of those bacteria that have strong foraging strategies and elimination of those that have poor foraging strategies occurs.

Chemotactic

The movement of *E Coli* bacteria in optimal direction by a fixed distance or height is accomplished with the help of locomotory organelles known as flagella by chemotactic movement in two ways. If a bacterium moves in same direction from previous one is called swimming and if bacterium moves in an absolutely different direction from previous one is called tumbling. Movement of Flagella in anticlockwise direction helps the bacteria to swim at very fast rate. Thus swimming and tumbling together known as chemotactic.

Swarming

When bacterium find its optimal position, it is desire that optimum bacterium should try to attract other bacteria by passing information about the nutrient concentration (optimal point) so that all the bacteria together converge the desired location very rapidly. Depending on the relative distance of each bacterium from fittest bacterium, a penalty function is added to original optimization function to find position of new bacteria. When all bacteria find their optimal position then penalty function becomes zero.

Reproduction

After getting evolution through several chemotactic steps and swarming, original set of bacteria is allowed to reproducing. Reproduction is a conjugation process in which bacteria is split into two identical bacteria. Reproduction is depends on health of bacteria. The least healthy bacteria from total population are eventually eliminated where as healthy bacteria will be split in two parts which are place at same location. During this reproduction process concentration of total bacteria remains constant.

Elimination/dispersal

During evolution process, elimination of set of bacteria is occurs and dispersed them into new environment. The new position of bacteria results in drastic alteration of biological process of evolution. The concept behind this process is to place a newer set of bacteria nearer to optimal location to avoid premature trapping into local optima instead of global optima known as stagnation.

Particle Swarm Optimization

PSO is a evolutionary optimization technique with implicit parallelism developed by Dr. Russel Eberhart & Dr. James kenned [12] in 1995 desired by bird flocking and fish schooling which can easily handled with non differential objective functions. PSO makes few or no assumptions about the problem being optimized and have capability of searching very large spaces of candidate solutions. Bird flocking optimize a certain objective function. A convenient solution for any problem can be evolved by set of potential solutions. Each particle searches for optimal position by changing its velocity according to rules by behavioral model of bird flocking with in a search space. Position of each particle provide a optimize solution. The define search space is shared by each individual. Individual may or may not modify their state based on following three factors:

- Fitness value.
- The individual previous history of states.
- Previous history of individual of neighborhood.

In PSO algorithm each individual is called particle and total population is called swarm. Particles are assumed to be volume less and are subjected to movement in multi dimensional space. There is no restriction for particles to hold at the same point in n-dimensional space but in any case their individuality shall be preserved. Development of PSO is through simulation of bird flocking in multi dimensional space. Each particle vector i.e. bird knows its best position called pbest and this position correspond to personal experience of each particle vector. Each particle vector knows best value in group gbest among pbest. Each particle tries to modify its position depend on following information

- Distance between current position and pbest.
- Distance between current position and gbest.

Each particle vector finds its best position and consists of components or strings as required number of normalized filter coefficients, depends on order of filter.

PSO is initialized with assigning random position and velocities to each bacterium. Particles have ability to move in any direction in n-dimensional space. A fitness/cost function is evaluated using this initial velocity and position. At each define time step, new function is evaluated with new coordinates based on previous value. Velocity and position of particle with each time step given as follow:

$$V_{id}(t+1) = w.V_{id}(t) + C_1.\phi_1.(P_{id}(t) - X_{id}(t)) + C_2.\phi_2.(P_{gd}(t) - X_{id}(t)) \quad (12)$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \quad (13)$$

On the other hand, BFOA is based on searching and foraging decision capability of E. Coli bacteria. The coordinate of each bacterium represents an individual solution. A set of trial solution converges towards finding optimal solution. Each bacterium continuously performing its chemotactic movement until bacterium finds its best fitness value (positive nutrient gradient). After undergoing chemotactic steps, each bacterium gets mutated by PSO. PSO have capability to exchange social information, unit length direction of tumble behavior is generated. If bacteria is moving randomly in any direction then this lead to delay to reach the optimal solution. In BF-PSO algorithm, tumble behavior of bacteria can be decided by global best position and best position of bacterium. It provides fast convergence speed compared with conveniently bacterial foraging and particle swarm optimization. Flow diagram of this proposed BF-PSO algorithm for search for optimal value of parameters is shown in figure 2 (Krone, 2008; Biswas, Dasgupta,

Das, Abralam, 2007; E. S. Ali, S. M. Abd-Elazim, 2013[13][14])

Procedure

Step1: Initialization : order of filter $M=21$ (odd filter), pass band cut-off frequency $\omega_p = 0.35$, pass band cutoff frequency $\omega_s = 0.01$, pass band ripple $\delta_p = 0.1$, stop band ripple $\delta_s = 0.01$, total number of coefficients = $M+1 = 22$, number of filter coefficients($h(n)$) to be determined are $(M+1)/2 = 11$, sampling points = 11

Initialization of BFO-PSO parameters: $p=12$, $S=26$, $N_c=5$, $N_s=14$, $N_{re}=4$, $N_{ed}=2$, $S_r= S/2$, $P_{ed}=0.24$, $C_1=5$, $C_2=0.5$.

Step 2: Generate randomly initial position and initial velocity of each bacteria. Also generate initial local and global best position of each bacterium.

Step 3: Compute initial fitness value of total population using live function (objective function) depends on initial positions, stop band and pass band cut-off frequency. Take this function as a last fitness function (J_{last}).

Step 4: Add a unit vector function in a last position to move bacteria in random direction. Take this as current position.

Step 5: While ($m < N_s$) Compute fitness function ($J_{current}$) using this new current position of bacteria. If this current fitness function is less than last fitness function ($J_{current} < J_{last}$) then replace last fitness function with new current fitness function i.e. $J_{last} = J_{current}$

Step 6: For each chemotactic movement evaluates the local (pbest) and global best position (gbest) that each bacteria move through it. Also update velocity and position of each bacterium as given in equation (12) and (13).

Step 7: Set the health of each of the S bacteria. Sort the nutrient concentration in order of ascending. And keep these chemotactic parameters with each bacterium for next generation. Split the bacterium. The least fit do not reproduce, the most fit split into two identical copies.

Step 8: Iteration continuous till the maximum iteration cycles or convergence of minimum error fitness values. Finally, pbest is the vector of filter coefficients

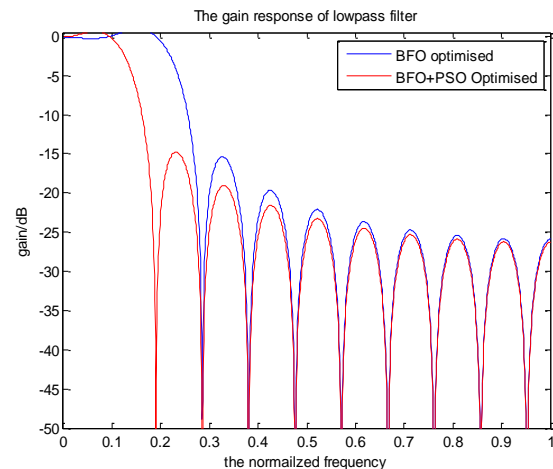
$((N+1)/2)$. Filter has linear phase remaining coefficients calculate by copying them.

Results and discussions

This section presents the simulation results performed in MATLAB 7.8.0(R2009a) for the design of digital FIR Low Pass Filter and effectiveness of proposed filter design method using BFO-PSO. The filter order (N) is taken as 21 which result in number of filter coefficients are 22. We need to optimized only 11 coefficients because FIR filter have linear phase and positive symmetry. Number of sampling points are 11. Sampling frequency is taken as 0.45.

The parameters for filter design using BFO-PSO are: pass band ripple (δ_p) = 0.1, stop band ripple (δ_s) = 0.01, pass band cutoff (edge) frequency (ω_p) = 0.35, stop band cutoff (edge) frequency (ω_s) = , transition width =0.45, order of filter is 21. Figure 3 shows dB plot (gain v/s frequency plot) for the LP Filter using BFO and BFO-PSO algorithms.

Figure 3: Magnitude (dB) plot of the FIR Low Pass Filter of order 21



Consider an input signal of different frequencies as shown in figure 4 is to be filtered out. Figure shows time domain characteristics and frequency domain characteristics of input signal. This signal contains three frequency band of frequencies $f_1=100$ Hz; $f_2=300$ Hz; $f_3=700$ Hz and sampling frequency $f_s=2000$ Hz. Figure 5 shows output filtered signal with time domain and frequency domain characteristics. Table 1 shows optimized filter coefficients using BFO and BFO-PSO optimization techniques.

Table 1: Optimized coefficients of FIR Low Pass Filter of order 21

h(N) (Filter Coefficients)	BFO Optimization	BFO-PSO Optimization
h(1)= h(22)	-1.049085	0.873022
h(2)=h(21)	0.199137	0.327770
h(3)= h(20)	-0.964994	-0.153733
h(4)= h(19)	0.772167	0.852975
h(5)= h(18)	0.420661	-0.346887
h(6)= h(17)	0.105352	-0.940938
h(7)= h(16)	0.530285	-0.042273
h(8)= h(15)	0.095504	-0.125716
h(9)= h(14)	0.297717	0.548252
h(10)= h(13)	0.264308	0.061161
h(11)= h(12)	0.305108	0.002469

Figure 4: Time domain and frequency domain characteristics of input signal before filtering

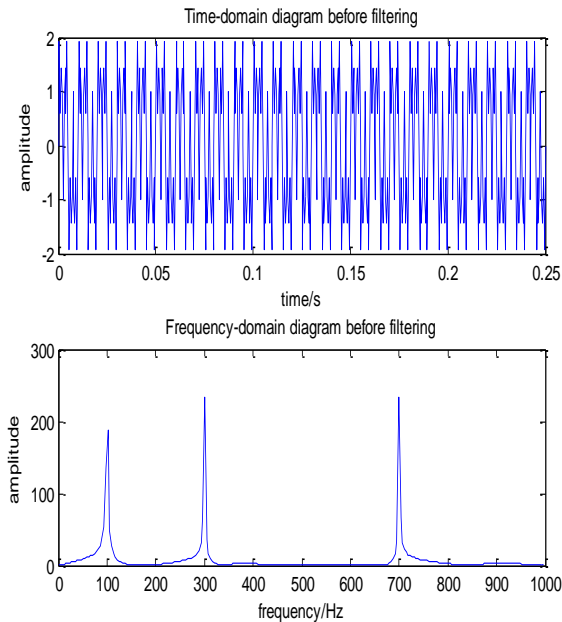
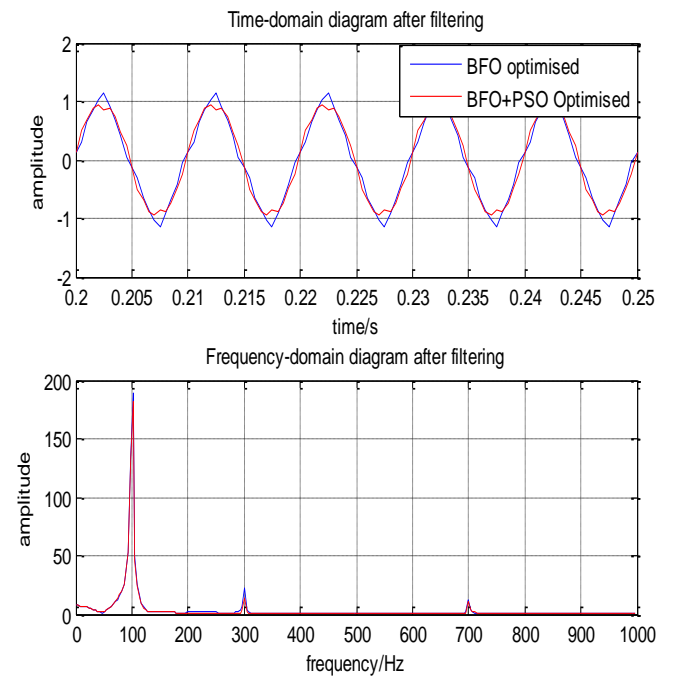


Figure 5: Time domain and frequency domain characteristics of output signal after filtering



Conclusion

In this paper, a Bacterial Foraging Optimization with Particle Swarm Optimization technique and conventional Bacterial Foraging Optimization are applied to find solution of the FIR low pass filter design problem with optimal filter coefficients. Filter of order 21 have been realized using BFO-PSO as well as BFO. The simulation results shows that combined approach of BFO and PSO provides better performance as compare to conventional BFO.

References

- [1] Passino, K. M., 2002, "Biomimicry of Bacterial Foraging for Distributed Optimization and Control", *IEEE Control System magazine*, pp. 52-67.
- [2] J. Kennedy and R. Eberhart, 2001, "Swarm Intelligence", Morgan Kaufmann Publishers.
- [3] J.I. Ababneh, Linear phase FIR filter design using particle swarm optimization and genetic algorithm, *Digital signal processing*, 18, 657-668, 2008.
- [4] L. Litwin, "FIR and IIR digital filters," *IEEE Potentials*, pp. 28-31, 2000.
- [5] Sangeeta Mondal, Vasundhara, Rajib Kar, Durbadal Mandal, S.P. Ghoshal, "High pass filter design using particle swarm optimization", *Vol:5*, pp. 12-26, 2011.

- [6] T.W. Parks, C.S. Burrus, *Digital filter design*, Wiley, New York.
- [7] Rajib Kar, Durbadal Mandal, Dibbendu Roy, Sakti Prasad Ghoshal, "FIR filter design using Particle Swarm Optimization with Constriction Factor and Inertia Weight Approach", Vol. 02, 2011.
- [8] T.W. Parks, J.H. McClellan, "Chebyshev approximation for non recursive digital filters with linear phase", *IEEE Trans. Circuits Theory*, CT-19, pp. 189-194, 1972.
- [9] Suman Kumar Saha, Rajib Kar and Durbadal Mandal, "Bacterial Foraging Optimization algorithm for FIR filter design", Vol. 5, No. 1, 2013.
- [10] Kim, D. H., Abraham, A., Cho, J. H., 2007, "A hybrid genetic algorithm and bacterial foraging approach for global optimization", *Information Science*, Vol 177 (18), pp. 3918-3937.
- [11] J. Kennedy and R. Eberhart, 2001, "Swarm Intelligence", Morgan Kaufmann Publishers.
- [12] J. Kennedy and R. Eberhart, 1995, "Particle Swarm Optimization", *IEEE International Conference on Neural Networks*.
- [13] Arijit Biswas, Sambatra Dasgupta, Swagatam Das, Ajith Abraham, 2007, "Synergy of PSO and BFO-A Comparative Study on Numerical Benchmarks", *International Symposium on Hybrid Artificial Intelligent System (HAIS)*, pp. 255-263.
- [14] Sushree Sangeeta Patnaik and Anup Kumar Panda, "Particle Swarm Optimization and Bacterial Foraging Optimization techniques for Optimal Current Harmonic Mitigation by Employing Active Power Filter", *Applied Computational Intelligence and Soft Computing*, Volume 2012, ID: 897127.