# Optimal Stable IIR Low Pass Filter Design Using Modified Firefly Algorithm

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**Abstract.** In this paper, a recently proposed global heuristic search optimization technique, namely, Modified Firefly Algorithm (MFFA) is considered for the design of the 8th order infinite impulse response (IIR) low pass (LP) digital filter. This modified version of FFA is considered to achieve quality output response by means of properly tuned control parameters over conventional Firefly Algorithm (FFA). Newly defined randomization parameter and modification in updating formula in MFFA makes it a perfect search tool in multidimensional search space. With this approach better exploration and exploitation are achieved, which have resulted in faster convergence to near global optimal solution. The performance of the proposed MFFA based approach is compared to the performances of some well accepted evolutionary algorithms such as particle swarm optimization (PSO) and real coded genetic algorithm (RGA). From the simulation study it is established that the proposed optimization technique MFFA outperforms RGA and PSO, not only in the accuracy of the designed filter but also in the convergence speed and the solution quality, i.e., the stop band attenuation, transition width, pass band and stop band ripples.

## 1 Introduction

In the signal processing system, filtering holds a significant position which is involved with manipulation by modifying, reshaping or transforming the spectrum of signal. Fundamentally, a filter operates on frequency domain to permit certain band of frequencies to pass through and attenuates others. The frequency at which such phenomenon happens is a design dependent parameter called cut-off frequency. This sort of frequency discrimination is of prime importance due to mixing of information carrying signal with noise. There are different sources of noise either created by nature or man-made effects. According to its frequency domain characteristics and source of generation, signals are mostly contaminated with thermal noise, shot noise, avalanche noise, flicker noise etc.

Most of the filters can be implemented with discrete components like resistor, capacitor, inductor and operational amplifiers when the input signal is continuous

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function of time and hence these are called analog filters. On the other hand a digital filter performs mathematical operations on a sampled, discrete time signal to reduce or enhance the desired features of the applied signal. Analog filters are replaced by digital filers due to their wide range of applications and superior performance. The advantages of digital filters over analog filters are small physical size, high accuracy, reliability and immune to component tolerance sensitivity [1].

Digital filters are of two types: finite impulse response (FIR) and infinite impulse response (IIR) filter. The order of the IIR filter is lower than that of the FIR filter for the same design specifications such as cut-off frequencies, pass band and stop band ripples and stop band attenuation. Hence, lesser number of delay elements and multipliers are required for hardware implementation and also lower computational time is required for software realization for IIR filter design [2].

Minimization of an objective function (typically the mean square error between desired response and estimated filter output) is often performed by gradient based iterative search algorithms. However, when the error surface (objective function) is multimodal and/or non-smooth, gradient-based optimization methods often cannot succeed in converging to the global minimum.

So, meta-heuristic evolutionary methods have been employed in the design of digital filters to design with better parameter control and to better approximate the ideal filter. Evolutionary optimization methods that require no gradient and can achieve a near global optimal solution offer considerable advantages in solving these multi-modal objective functions in digital filter design problem.

Different heuristic search techniques are reported in the literature. These are GA [3-4], Seeker optimization Algorithm (SOA) [5], orthogonal genetic algorithm (OGA) [6], hybrid Taguchi GA (TGA) [7], Tabu search [8], Simulated Annealing (SA) [9], Bee Colony Algorithm (BCA) [10], Differential Evolution (DE) [11], Cat swarm Optimization [12], Artificial Immune Algorithm [13], particle swarm optimization (PSO) [14-16], Gravitational search algorithm (GSA) [17-18], Opposition based BAT algorithm (OBA) [19], Firefly algorithm (FFA) [20-25] etc.

The approach detailed in this paper takes advantage of the power of the stochastic global optimization technique called modified Firefly algorithm (MFFA). Although the algorithm is adequate for applications in any kind of parameterized filters, the authors have chosen to focus on real-coefficient IIR filters. The basic Firefly algorithm is very efficient. It is suitable for parallel implementation because different fireflies can work almost independently. But it is observed from the simulation results that the solutions are still changing as the optima are approaching. To improve the solution quality, randomness is reduced so that the algorithm could converge to the optimum more quickly [26]. Apart from normal FFA the modifications considered in MFFA are as follows. In FFA, randomization parameter is a random number but in MFFA it is a gradually decreasing function of iteration cycle and in position updating formula, position of the group best firefly is taken into consideration for the calculation of new position of any firefly. With these modifications the solution obtained is much close to the global optimal solution with less number of iteration cycles.

## 2 Low Pass IIR Filter Design

This section presents the design strategy of IIR filter based on MFFA. The input-output relation is governed by the following difference equation [2]:

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

where *x(p)* and *y(p)* are the filter's input and output, respectively, and $n(\geq m)$ is the filter's order. The transfer function of IIR filter with the assumption $a_0 = 1$ is expressed as in (2).

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

Let $z = e^{j\Omega}$. Then the frequency response of the IIR filter becomes

$$H(z)=\frac{\sum_{k=0}^{m}b_k e^{-jk\Omega}}{1+\sum_{k=1}^{n}a_k e^{-jk}\Omega} \tag{3}$$

or, $$H(\Omega)=\frac{Y(\Omega)}{X(\Omega)}=\frac{b_0+b_1e^{-j\Omega}+\ldots+b_m e^{-jm\Omega}}{1+a_1e^{-j\Omega}+\ldots+a_n e^{-jn\Omega}} \tag{4}$$

where $\Omega=2\pi(f/f_s)$ is the digital frequency, $f$ is the analog frequency, and $f_s$ is the sampling frequency. The commonly used approach to IIR filter design is to represent the problem as an optimization problem with the mean square error (MSE) as the error fitness function, $J(\omega)$ expressed as in (5) [4].

$$J(\omega)=\frac{1}{N_s}[(d(p)-y(p))^2] \tag{5}$$

where $N_s$ is the number of samples used for the computation of the error fitness function; *d(p)* and *y(p)* are the filter's desired and actual responses. The difference *e(p)=d(p)-y(p)* is the filter's error signal. The design goal is to minimize the value of error fitness function $J(\omega)$ with proper adjustment of coefficient vector $\omega$ represented as: $\omega=[a_0a_1\ldots a_n\ b_0b_1\ldots b_m]^T$. In this paper, an improved error fitness function given in (6) is adopted in order to achieve higher stop band attenuation and to have more control on the transition width. Using (6), it is found that the proposed filter design approach results in considerable improvement in stop band attenuation over other optimization techniques.

$$J_1(\omega) = \sum_{\omega} abs\left[abs\left(\left|H_d(\omega)\right| - 1\right) - \delta_p\right] + \sum_{\omega}\left[abs\left(\left|H_d(w)\right| - \delta_s\right)\right] \tag{6}$$

For the first term of (6), $\omega \in$ pass band including a portion of the transition band and for the second term of (6); $\omega \in$ stop band including the rest portion of the transition band. The portions of the transition band chosen depend on pass band edge and stop band edge frequencies.

The error fitness function given in (6) represents the generalized fitness function to be minimized using the evolutionary algorithms RGA, conventional PSO and the proposed MFFA, individually. Each algorithm tries to minimize this error fitness $J_1$ and thus optimizes the filter performance. Unlike other error fitness functions as given in [4], $J_1$involves summation of all absolute errors for the whole frequency band, and hence, minimization of $J_1$ yields much higher stop band attenuation and lesser pass band ripples.

# 3 Evolutionary Techniques Employed

## 3.1 Firefly Algorithm (FFA)

Evolutionary techniques RGA and PSO are used to make a comparative study of the results obtained with the proposed optimization technique MFFA and the detailed discussions regarding RGA and PSO are available in [27-28].

### 3.1.a Behaviour of Fireflies

The flashing light of fireflies which is produced by a bioluminescence process constitutes a signaling system among them for attracting mating partners or potential preys. It is interesting to know that there are about two thousand species of fireflies around the world. Each has its own pattern of flashing. As we know, the light intensity at a particular distance $r$ from the light source obeys the inverse square law. That is to say, the light intensity $I$ decreases as the distance $r$ increases in terms of $I \alpha \frac{1}{r^2}$. Furthermore, the air absorbs light. These two combined factors make most fireflies visual to a limit distance.

FFA, developed by Yang [29], is inspired by the flash pattern and characteristics of fireflies. The basic rules for FFA are:

i. All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex;
ii. Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less bright one will move towards the brighter one, and the brightness decreases as their distance increases. If there is no brighter one than a particular firefly, it will move randomly;
iii. In this work, the brightness of a firefly is affected or determined by the landscape of the cost function. For a minimization problem, the brightness can simply be inversely proportional to the value of the cost function. The cost function is the error fitness function $J_1$ in this work.

### 3.1.b Light Intensity and Attractiveness

The variation of light intensity and formulation of the attractiveness are two important issues in the firefly algorithm. The attractiveness $\beta$ is proportional; it should be seen in the eyes of the beholder or judged by the other fireflies. Thus it will vary with the distance $r_{ij}$ between firefly $i$ and firefly $j$. In addition, light intensity decreases with the distance from its source, and light is also absorbed in the media, so the attractiveness will also vary with the degree of absorption. The combined effect of both inverse square law and absorption can be approximated as the following Gaussian form as (7). Hence, the attractiveness function $\beta(r)$ can be any monotonically decreasing function such as the following generalized form:

$$\beta(r) = \beta_0 e^{-\gamma r^m} \qquad (m \geq 1) \tag{7}$$

where $r$ is the distance between two fireflies, $\beta_0$ is the attractiveness at $r=0$, and $\gamma$ is a fixed light absorption coefficient which can be used as a typical initial value. In theory, $\gamma \in [0, \infty]$ but in practice $\gamma$ is determined by the characteristic length of the system to be optimized. In most applications it typically varies from 0.1 to 1. Characteristic distance $\Gamma$ is the distance over which the attractiveness changes significantly. For a given length scale, the parameter $\gamma$ can be chosen according to:

$$\gamma = \frac{1}{\Gamma^m} \tag{8}$$

The distance between any two fireflies $i$ and $j$ at $x_i$ and $x_j$, respectively, is the Euclidean distance as follows:

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k}\right)^2} \tag{9}$$

where $x_{i,k}$ is the $kth$ component of the $i$th firefly ( $x_i$ ). The movement of a $i$th firefly that is attracted to another more attractive (brighter) $j$th firefly $j$, is determined by the following equation which shows the relation between the new position of the $i$th firefly ($x'_i$) and its old position ($x_i$):

$$x_i^{'} = x_i + \beta_0 e^{-\gamma r^2} (x_j - x_i) + \alpha \varepsilon_i \tag{10}$$

where the second term is due to the attraction. The third term is randomization, with $\alpha \in [0,1]$ being the randomization parameter, and $\varepsilon_i$ a vector of numbers drawn from a Gaussian distribution or uniform distribution.

### 3.1.c Modified Firefly Algorithm (MFFA)

The basic Firefly algorithm is very efficient. It is suitable for parallel implementation because different fireflies can work almost independently. To improve the solution quality, randomness is reduced so that the algorithm could converge to the optimum solution more quickly. Hence, the randomization parameter $\alpha$ decreases gradually as the optima are approaching.

$$\alpha = \alpha_{\infty} + (\alpha_0 - \alpha_{\infty})e^{-t} \tag{11}$$

where $t \in [0, t_{\max}]$ is the pseudo time for simulation and *t*max is the maximum number of generations. $\alpha_0$ is the initial randomization parameter while is the final value. In addition, an extra term $\lambda\varepsilon_i(x_i - g_{best})$ is added to the updating formula [26]. In the simple version of the FFA, the current global best *gbest* is only used to decode the final best solutions. The modified updating formula for firefly position is shown in (12).

$$x_i^{'} = x_i + \beta_0 e^{-\gamma r^2}(x_j - x_i) + \alpha\varepsilon_i + \lambda\varepsilon_i(x_i - g_{best}) \tag{12}$$

### 3.1.d Steps of Implementation of MFFA to the Design of Low Pass IIR Filters

Steps of MFFA are as follows:

Step 1: Generate initial firefly vectors xi = (xi1,...,xiD) (D = 1,...,18; i=1,…,25). Set the maximum allowed number of iterations to 500; $\beta_0$ = 0.6; $\gamma$ = 0.2; and $\alpha$ = 0.01; the population size=25; These values were determined as the best values in a series of thirty preliminary trials.

Step 2: Computation of $J_1$ values of the total population.

Step 3: Computation of the initial population based best solution (gbest) vector corresponding to the historical population best and least $J_1$ value.

Step 4: Update firefly positions:

(a) Compute square root (rsqrt) of Euclidian distance between the first particle vector and the second particle vector as per (9);

(b) Compute $\beta$ with the help of $\beta_0$ as per (7) and update $\alpha$ as per (11);

(c) If $J_1$ of second particle is < $J_1$ of first particle, then, update the first particle as per (12) with $+\beta_0$ (case of attraction), otherwise with $-\beta_0$, (case of repulsion);

(d) Update firefly position as per (12).

Step 5: Repeat Step 2 till maximum iteration cycles.

The values of the parameters used for RGA, PSO and MFFA techniques are given in Table I.

# 4 Simulation Results and Discussions

## 4.1 Analysis of Magnitude Response of Low Pass IIR Filters

In this paper digital IIR filters are implemented by MATLAB programs and the best simulation results are reported among thirty independent program runs.

**Table 1.** Control Parameters of RGA, PSO and MFFA

| Parameters | RGA | PSO | MFFA |
|---|---|---|---|
| Population size | 120 | 25 | 25 |
| Iteration Cycle | 500 | 500 | 600 |
| Crossover rate | 1 | - | - |
| Crossover | Two Point Crossover | - | - |
| Mutation rate | 0.01 | - | - |
| Mutation | Gaussian Mutation | - | - |
| Selection | Roulette | - | - |
| Selection Probability | 1/3 | - | - |
| $C_1$ | - | 2.05 | - |
| $C_2$ | - | 2.05 | - |
| $v_i^{min}$ | - | 0.01 | - |
| $v_i^{max}$ | - | 1.0 | - |
| $\alpha$, $\lambda$, $\beta_0$ | - | - | 0.01, 0.2, 0.6 |

In this simulation study, equal numbers of numerator and denominator coefficients are considered for 8th order IIR filter. Hence, 18 coefficients are optimized using each algorithm under consideration , independently and their performances are presented for making a comparative study among the algorithms. The parameters of the low pass filter to be designed are: the sampling frequency $f_s$ = 1Hz; Sampling number is taken as 128; Pass band ripple (δp) = 0.001, Stop band ripple (δs) = 0.0001, pass band normalized edge frequency ($\omega_p$) = 0.45, stop band normalized edge frequency ($\omega_s$) = 0.50. The control parameters' values of RGA, PSO and MFFA used in this work are given in Table 1. Each algorithm is run for thirty times to get its best solutions. The best results are reported in this paper.

Figure 1 shows the gain plot in dB for the designed low pass 8th order IIR filter. Figure 2 shows the normalized gain plot of the 8th order low pass IIR filter. The best optimized denominator coefficients $a_k$ and numerator coefficients $b_k$ for the designed filter have been calculated using RGA, PSO and MFFA and are given in Table 2. Table 2 also shows that the maximum stop band attenuations achieved for the designed IIR filters using RGA, PSO and MFFA are 27.5145 dB, 30.3635 dB, 37.5474 dB, respectively. Pole-zero plots can be obtained with the filter coefficients reported in Table 2 and in Figure 3, the pole-zero plot obtained for the proposed optimization technique MFFA is only reported. From Figure 3, it is evident that the filter designed using the MFFA is stable as the poles are located within the unit circle.

**Table 2.** Optimized Coefficients and Performance Comparison of Different Algorithms

| **Algorithms** | **Numerator Coefficient ($b_k$)** | **Den. Coeff. ($a_k$)** | **Max. stop Band Attenuation (dB)** |
|---|---|---|---|
| RGA | 0.0415 0.1234<br>0.2676 0.3806<br>0.4206 0.3484<br>0.2164 0.0925<br>0.0233 | 0.9994 -1.1555<br>2.7421-2.3022<br>2.4552 -1.4037<br>0.7776 -0.2480<br>0.0524 | 27.5145 |
| PSO | 0.0413 0.1241<br>0.2668 0.3791<br>0.4202 0.3478<br>0.2165 0.0936<br>0.0235 | 1.0001 -1.1546<br>2.7413 -2.3016<br>2.4547 -1.4044<br>0.7781 -0.2483<br>0.0519 | 30.3635 |
| MFFA | 0.0303 0.0784<br>0.1688 0.2386<br>0.2710 0.2328<br>0.1589 0.0730<br>0.0256 | 1.0002 -1.6893<br>3.3759 -3.4280<br>3.2821 -2.0259<br>1.0293 -0.3239<br>0.0598 | 37.5474 |

**Table 3.** Qualitatively Analyzed Data for the 8th Order IIR LP Filter

| Algo-rithm | Maximum Pass band ripple (normalized) | Stop band ripple (normalized) | | | Transition Width |
|---|---|---|---|---|---|
| | | Maximum ($\times 10^{-2}$) | Minimum ($\times 10^{-4}$) | Mean ($\times 10^{-2}$) | |
| RGA | 0.0095 | 4.2100 | 15.7130 | 2.1836 | 0.0297 |
| PSO | 0.0021 | 3.0300 | 6.2811 | 1.5464 | 0.0338 |
| MFFA | 0.0024 | 1.2400 | 3.9563 | 0.6398 | 0.0319 |

The locations of the zeros, as shown in Figure 3, are positioned outside the unit circle, which implicitly states the system as a non-minimum phase system. Qualitatively analyzed data obtained from Figures 1-2 are reported in Table 3 for all concerned optimization techniques. From Figures 1-2, it is evident that the proposed MFFA based IIR filter design approach produces the highest stop band attenuation and the smallest stop band ripple compared to other optimization techniques. It is also to be noted from Table 3 that the filter designed by the MFFA technique yields quite small transition width, which implies the moderately fast change over from pass band to stop band. The aforementioned statements can be verified from the results presented in Table 3. For both the stop band and pass band regions, the filter designed by the MFFA method results in the improved response than the others.

### 4.2 Comparative Effectiveness and Convergence Profiles of RGA, PSO and MFFA

In order to compare the algorithms in terms of the error fitness values, Figures 4-5 show the plots of error fitness values against the number of iteration cycles when RGA, PSO and MFFA are employed, respectively, for the design of 8th order IIR low pass filter. From the aforementioned figures, it is seen that the MFFA technique takes 562 iteration cycles to attain the error value of 1.925; whereas, 361 and 359 iteration cycles are required to achieve error values of 2.85 and 4.054 for PSO and RGA techniques, respectively. With a view to the above fact, it may finally be inferred that the performance of the MFFA technique is better as compared to RGA and PSO in terms of the lowest error fitness value in designing the optimal IIR filter. All optimization programs were run in MATLAB 7.5 version on core (TM) 2 duo processor, 3.00 GHz with 2 GB RAM.

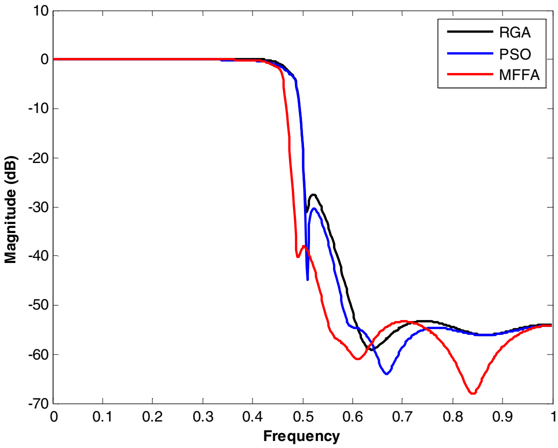


**Fig. 1.** Gain Plot in dB for the 8th order low pass IIR Filter

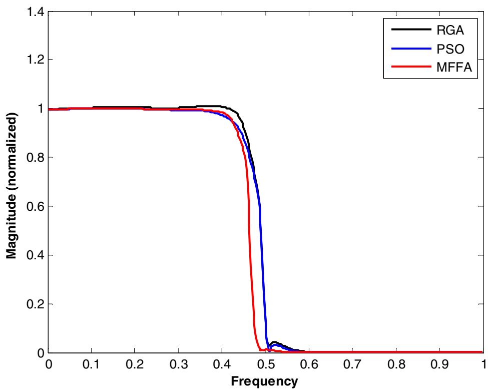


**Fig. 2.** Normalized gain plot for the 8th order low pass IIR Filter

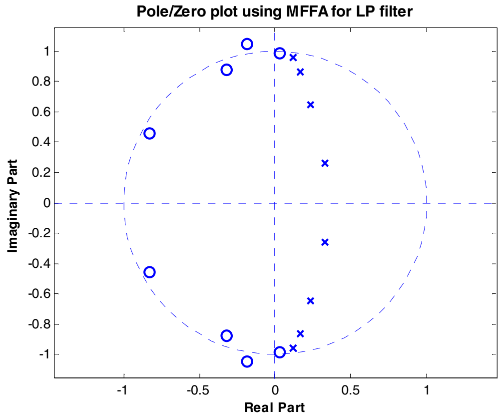


**Fig. 3.** Pole-Zero plot for the 8th order low pass IIR filter using the MFFA

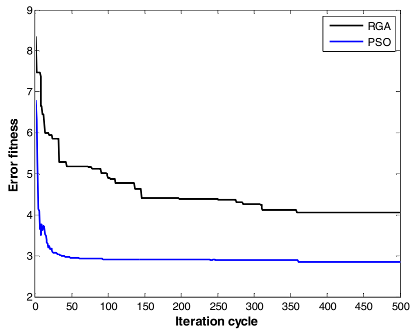


**Fig. 4.** Convergence profiles for RGA and PSO for the 8th order low pass IIR filter

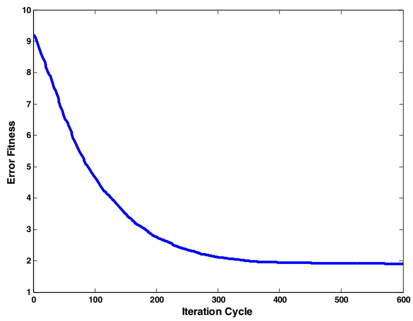


**Fig. 5.** Convergence profile for the MFFA for the 8th order low pass IIR filter

## 5 Conclusions

In this paper a recently proposed heuristic search algorithm MFFA is used for the design of IIR LP filter. The modifications adopted in random parameter and position updating process implemented in the MFFA result in better exploration and exploitation of the search space along with the convergence to near-optimal solution. A comparative study between the proposed technique and other well accepted algorithms RGA and PSO affirms that the proposed MFFA based design technique not only provides the highest stop band attenuation but also the quality output in terms of ripples and transition width, which are much better than others. Also the proposed technique attains the lowest value of error fitness function within minimum number of iteration cycles and hence the MFFA is adequate enough for handling other related filter design problems.

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