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Flower Pollination Algorithm Approach Towards IIR System Identification

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Abstract

This paper proposes a novel evolutionary optimization technique referred to the flower pollination algorithm (FPA) for system identification. The optimal parameters of an unknown infinite impulse response (IIR) system are computed using FPA. This algorithm is inspired by the pollination process of flowers. Proper tuning of control parameter has been performed in order to accomplish a balance between intensification and diversification phases. The proposed FPA based method for system identification is free from the problems of premature convergence and sub-optimal solutions, encountered in conventional methods. To validate the performance of FPA based system identification, simulations has been carried out for two benchmarked IIR systems of same order. Mean square error and convergence profile are the performance parameters used to evaluate the performance of the proposed method. Simulated results demonstrate that, the FPA based system identification gives superior performance over particle swarm optimization.

Keywords: *Adaptive filtering, Flower pollination algorithm (FPA), Particle swarm optimization (PSO), System identification*

1. Introduction

In recent years, adaptive filtering is a protruding field of research and has been extensively used in the field of control systems [1], prediction, radar processing, robotics [2], system identification and modeling [3], signal processing, speech processing and communication systems [4]. This is because an adaptive infinite impulse response (IIR) system can be described more effectively with a lessor number of parameters as compared to a finite impulse response (FIR) system [5]. An unknown physical system can be modeled more accurately using IIR system, with less number of coefficients or require a lower order to meet a particular level of performance as compared to the corresponding FIR system.

The two major requirements of efficient realization of adaptive IIR system identification problem are the computation of finest system parameters and the choice of identification structure. Therefore, the system identification problem can be modeled as an estimate problem. The objective is to compute the optimal set of parameters such that output of the adaptive IIR system matches exactly with the output of the unknown system provided that both systems are given same input. From past few decades, gradient search method and evolutionary optimization methods are basically two methods that are adopted by various scholars to resolve system identification problem. Some of the commonly used gradient search methods include Quesi-Newtons method and least mean squares (LMS) method. As the IIR system identification problem is the error minimizing problem, these methods get struck in local optima solution and not proficient to compute the global optimal solution. Some other limitations of these methods that make them inappropriate for the system

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identification are: (i) required continuous and linear fitness, (ii) locally optimal system parameters are obtained, (iii) capable to handle small search space, (iv) highly sensitive to the initial solutions.

The above mentioned inadequacies of conventional methods inspired the researcher to exploit the evolutionary algorithms for the system identification problem. In last two decades, evolutionary algorithms have been successfully applied for solving various engineering applications like filter design [6], order reduction LTI system design [7], fractional delay filters design [8], fractional order differentiator design [9] and system identification [10]. The system identification problem is solved by different practitioners using genetic algorithm (GA) [11], particle swam optimization (PSO) [12], gravitational search algorithm (GSA) [13], cat swarm optimization (CSO) [14], differential evolution (DE) [15], opposition-based bat algorithm (OBA) [16], firefly algorithm (FA) [17], cuckoo search algorithm (CSA) [18], hybrid particle swarm optimization and gravitational search algorithm (HPSO-GSA) [19].

Yao and Sethares applied genetic algorithm for the parameter estimation of both linear and nonlinear systems [11]. In [12], Chen and Luk used the particle swarm optimization for designing of the digital IIR filter. Rashedi *et al.*, used gravitational search algorithm for solving the system identification problem for both linear and nonlinear system [13]. Panda *et al.*, presented that the performance of cat swarm optimization is superior in identifying the IIR systems as compared to that of GA and PSO for both the same order and reduced order system [14]. In 2005, Karaboga utilized differential evolution algorithm for adaptive IIR system identification problem. Simulation result confirms the superior performance of DE based IIR filter compared to GA [15]. Saha *et al.*, introduced opposition-based BAT algorithm that is used to calculate the optimal filter coefficients for IIR system identification problem [16]. Upadhyay *et al.*, reported an IIR system identification problem in which the filter coefficients are optimized using firefly algorithm. Patwardhan *et al.*, investigated IIR filter for system identification using cuckoo search algorithm [18]. Jiang *et al.*, presented a hybrid particle swarm optimization and gravitational search algorithm combining the best features of PSO and GSA that is further utilized to compute the optimal parameters of an unknown IIR system with same order and reduced order system [19].

In this paper, performance of the flower pollination algorithm is examined for IIR system identification using two benchmark IIR systems with same order system. Simulation results obtained from the FPA are compared with PSO to demonstrate the efficacy of FPA for system identification. The effectiveness of the FPA is assessed by optimal system parameters, mean square error and convergence profile.

The rest of the paper is organized as follows. Section II introduces the mathematical formulation of IIR system identification problem. The brief explanation of flower pollination algorithm is presented in Section III. In Section IV, simulation results have been presented for two standard test functions to evaluate the performance of FPA for system identification. Finally, conclusion is drawn in Section V.

2. System Identification

The basic concepts of IIR system identification are reviewed briefly in this section. System identification is the process of determining a mathematical model for an unknown system by varying its input-output parameters using the evolutionary algorithm. Here, the coefficients of the adaptive IIR filter is varied until and unless the output of the unknown system matches closely with the IIR filter output, when both the system are subjected to same input. The adaptive algorithm tries to vary the adaptive IIR filter coefficients such that the error between the output of the unknown system and adaptive IIR system output is minimized. Figure 1 shows the block diagram of the adaptive IIR system identification problem using optimization algorithms.

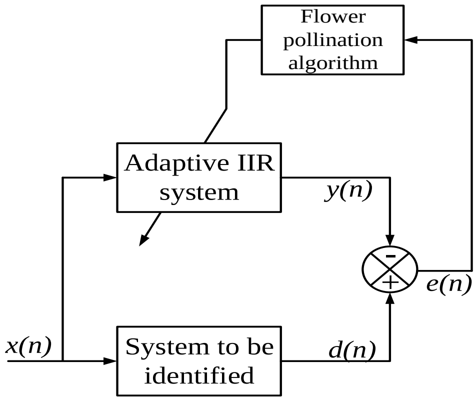

Figure 1. Block Diagram of Adaptive IIR Filter for System Identification

The input-output relation of IIR system is given by

$$y(n)+\sum_{i=1}^{N}a_i y(n-i)=\sum_{i=0}^{M}b_i x(n-i) \tag{1}$$

Table 1. Control Parameters of PSO and FPA for IIR System Identification

Parameters	PSO	FPA
Population size	20	20
Maximum iterations	500	500
C_1	2.0	−
C_2	2.0	−
v_i^{min}	0.01	−
v_i^{max}	1.0	−
w_{min}	0.2	−
w_{max}	1.0	−
Switch Probability	−	0.8

where $x(n)$ and $y(n)$ are the filter input and output, respectively; N and M are the order of numerator and denominator, respectively. Supposing the value of coefficient $a_0 = 1$, the transfer function of the adaptive filter is given as

$$H(z)=\frac{\sum_{i=0}^{M}b_i z^{-i}}{1+\sum_{i=1}^{N}a_i z^{-i}} \tag{2}$$

The basic idea of system identification is to compare the actual system response with the estimated system responses based on an objective function. Here, the objective function is the mean square error (MSE). The main goal of this work is to minimize the MSE with the proper adjustment of coefficients value so that the error between the estimated model response and actual model response is minimized. The objective function MSE is given as follows:

$$J=E(e^2(n))=\frac{1}{L}\sum_{i=1}^{L}(d(n)-y(n))^2 \tag{3}$$

where L is total length of data used for parameter estimation and $e(n)$ is the error signal between output responses of the unknown system and adaptive IIR system.

3. Flower Pollination Algorithm

Flower pollination is a motivating process. Yang [20] introduced Flower pollination algorithm in 2012. Inspiration behind this algorithm is the pollination process of flowers. The FPA can be used to solve optimization problems with or without constraints [21]. Pollination helps in the reproduction of plants that takes place by union of gametes. The pollen grains produced by male gametes and ovules borne by female gametes. It is essential that the pollen has to be transferred to the stigma for the union.

This process of union of pollen grains with ovule in ovary of flower is called as pollination. The process takes place with the aid of agents or pollinating agents or pollinators. There are two types of pollination namely Self-pollination and Cross pollination. The self-pollination happens within the plant so there is no need of pollinating agents such as insects, whereas cross pollination occurs between two different plants, so agents are required to achieve the same.

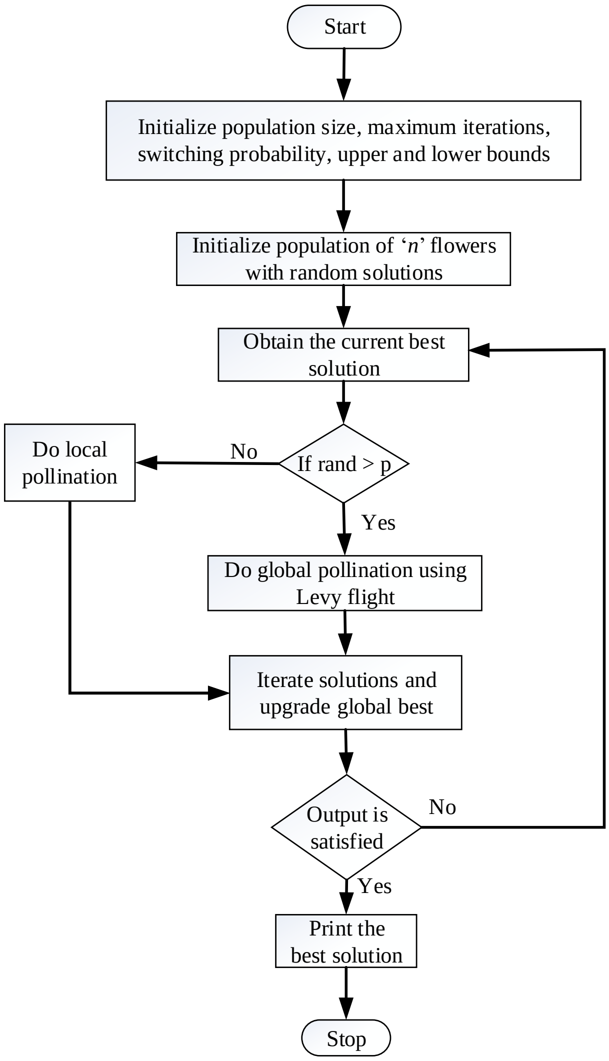

Figure 2. Flow Chart of Flower Pollination Algorithm

For venerating the characteristics of pollination certain rules were articulated:

a) Biotic and cross-pollination is considered as global pollination process with pollen-carrying pollinators performing Levy flights.

b) Abiotic and self-pollination are considered as local pollination.

c) Flower constancy can be considered as the reproduction probability and is proportional to the similarity of two flowers involved.

d) Local pollination and global pollination is controlled by a switch probability $p \in [0,1]$.

For the implementation of FPA a population $X^t(X_1^t, X_2^t, \ldots, X_N^t)$ of N flower positions is developed from the initial position at $t = 0$ to a total number of iterations. In FPA, to generate the new population the two operators namely local and global pollination operators are used. One is local pollination and another is global pollination. For the selection of operators, a factor p is used. So to select one of the two operators a random number *rand* is generated in the range [0,1]. If *rand* is less than p, the global pollination operator is applied to the current position X_i^t of flower. Otherwise, the local pollination is employed. Initially p is taken as 0.5 but $p = 0.8$ gives the best performance for most of the identification problems.

In global pollination operator, flower pollens are carried by pollinators such as insects, and pollens can travel over a long distance because insects can fly in random motions for long range of distances. The original position is disturbed to a new position according to following equation:

$$X_i^{t+1} = X_i^t + L(X_i^t - g^*) \tag{4}$$

where, X_i^t is the initial position of flower and X_i^{t+1} the displaced position at t^{th} iteration. g^* is the global best position found among all solutions. The parameter L is the step size and is given by Levy distribution to imitate the natural flight trajectory of pollinators.

$$L = \lambda\Gamma(\lambda)\sin(\pi\lambda/2)/\pi)(s^{\lambda+1}) \tag{5}$$

The local pollination can be represented by the following equation:

$$X_i^{t+1} = X_i^t + \varepsilon(X_j^t - X_k^t) \tag{6}$$

where X_j^t and X_k^t are the positions of flowers chosen randomly. ε is the random number between [-1,1]. The flowchart of FPA for the unknown system identification is shown in Figure 2.

4. Simulation Results

Comprehensive simulations have been done for the performance evaluation of an unknown system identification problem using PSO and FPA algorithms. Two standard benchmark system functions are considered to evaluate the performance of this applied algorithm. Here, the unknown system and benchmark system are of same order. The simulated results have been compared in terms of mean square error and convergence profile. Extensive simulations have been carried out with different set of control parameters of applied algorithm.

Table 1 describe the optimal set of control parameters that result in best for system identification problem.

Example 1 A fifth order system is considered as discussed in [19] and its transfer function is given by

$$H(z) = \frac{0.1084 + 0.5419z^{-1} + 1.0837z^{-2} + 1.0837z^{-3} + 0.5419z^{-4} + 0.1084z^{-5}}{1 + 0.9853z^{-1} + 0.9738z^{-2} + 0.3864z^{-3} + 0.1112z^{-4} + 0.0113z^{-5}} \tag{7}$$

This fifth order system is modeled using a fifth order unknown system with transfer function

$$H_{af}(z) = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2} + b_3 z^{-3} + b_4 z^{-4} + b_5 z^{-5}}{1 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3} + a_4 z^{-4} + a_5 z^{-5}} \tag{8}$$

Table 2. Optimal Coefficients for Example 1 Modelled using Fifth Order IIR System

Value	Algo.	Numerator coefficients						Denominator coefficients				
		b_0	b_1	b_2	b_3	b_4	b_5	a_1	a_2	a_3	a_4	a_5
Actual value		0.1084	0.5419	1.0837	1.0837	0.5419	0.1084	0.9853	0.9738	0.3864	0.1112	0.0113
Estimated value	PSO	0.1089	0.5357	1.0523	1.0187	0.4769	0.0753	0.9282	0.9098	0.3309	0.0895	0.0073
	FPA	0.1083	0.5361	1.0745	1.0789	0.5349	0.1020	0.9798	0.9594	0.3800	0.1050	0.0119

Table 3. Statistical Analysis of MSE in Example 1 Modelled using Fifth Order IIR System

Algorithm	MSE				
	Best	Worst	Average	Median	Standard deviation
PSO	7.7470 x 10^{-04}	2.3963 x 10^{-02}	5.7836 x 10^{-03}	1.2613 x 10^{-03}	1.0107 x 10^{-02}
FPA	1.3417 x 10^{-05}	2.5000 x 10^{-03}	3.5630 x 10^{-04}	5.7500 x 10^{-05}	7.7120 x 10^{-04}

The objective is to optimize the numerator and denominator coefficients b_0, b_1, b_2, b_3, b_4, b_5 and a_1, a_2, a_3, a_4, a_5 respectively, of the unknown system such that their values approach the standard benchmark function. The coefficients that lead to the best approximation to the fifth order unknown system using PSO and FPA are summarized in Table II. From the observation of Table 2, it can be concluded that the FPA gives the best approximation to the unknown system coefficients compared to and PSO. To assess the performance of applied algorithm, statistical analysis in terms of best, worst, average and standard deviation is performed on mean square error (MSE). The observed values of MSE for PSO and FPA are reported in Table 3. The best MSE values obtained are 7.7470 x 10^{-04} and 1.3417 x 10^{-05} for PSO and FPA, respectively. It is evident from the observation of Table 3 that the proposed FPA based system identification method yields the best results in terms of MSE as compared with PSO.

Example 2 A sixth order system is considered as referred in [19] and its transfer function is given by

$$H(z) = \frac{1 - 0.4z^{-2} - 0.65z^{-4} + 0.26z^{-6}}{1 - 0.77z^{-2} - 0.8498z^{-4} + 0.6486z^{-6}} \tag{9}$$

This sixth order system is modeled using a sixth order unknown system with transfer function

$$H_{af}(z) = \frac{b_0 + b_2 z^{-2} + b_4 z^{-4} + b_6 z^{-6}}{1 + a_2 z^{-2} + a_4 z^{-4} + a_6 z^{-6}} \tag{10}$$

The objective is to optimize the numerator and denominator coefficients b_0, b_2, b_4, b_6 and a_2, a_4, a_6 respectively, of the unknown system such that their value approaches the standard benchmark function. The coefficients that lead to the best approximation to the sixth order unknown system using PSO and FPA are reported in Table 4. From the observation of Table 4, it can be inferred that the FPA gives the best approximation to the unknown system coefficients compared to PSO. To evaluate the performance of applied algorithm, statistical analysis in terms of best, worst, average median and standard deviation is performed on mean square error. The noted values of MSE for PSO and FPA are given in Table V. The best MSE values observed are 2.3757 x 10^{-04} and 1.9799 x 10^{-04} for PSO and FPA, respectively. It is apparent from the observation of Table 5 that the proposed FPA based system identification method yields the best results in terms of MSE as compared with PSO.

Table 4. Optimal Coefficients for Example 2 Modelled using Sixth Order IIR System

Value	Algorithm	Numerator coefficients				Denominator coefficients		
		b_0	b_2	b_4	b_6	a_2	a_4	a_6
Actual value		1.0000	-0.4000	-0.6500	0.2600	-0.7700	-0.8498	0.6486
Estimated value	PSO	1.0000	-0.2992	-0.6137	0.2181	-0.6632	-0.8516	0.5572
	FPA	1.0000	-0.4023	-0.6525	0.2621	-0.7723	-0.8509	0.6516

Table 5. Statistical Analysis of MSE in Example 2 Modelled Using Sixth Order IIR System

Algorithm	MSE				
	Best	Worst	Average	Median	Standard deviation
PSO	2.3757 x 10^{-04}	8.8234 x 10^{-03}	3.8091 x 10^{-03}	2.5575 x 10^{-03}	3.5361 x 10^{-02}
FPA	1.9799 x 10^{-04}	6.2950 x 10^{-03}	3.700 x 10^{-03}	3.100 x 10^{-03}	3.600 x 10^{-03}

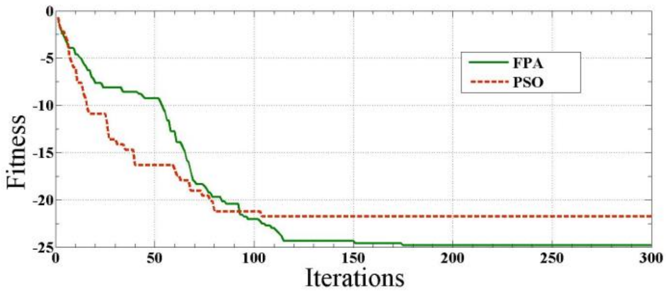

Figure 3. Convergence Profile using FPA and PSO

Figure 3 demonstrates the convergence profile for the least MSE values using PSO and FPA. It is evident from Figure 3 that FPA converges very fast to the minimum fitness value compared to PSO.

5. Conclusions

In this paper, to accomplish precise identification of the IIR system, FPA based optimization algorithm is used. To evaluate the performance of FPA for the problem under consideration, simulations using MATLAB are carried out for two standard IIR systems. MSE and convergence profile are taken as the two performance measures for the unknown IIR system identification. Simulated results confirm that FPA illustrate superior ability for system identification as compared to PSO. Further, the effort can be extended for the identification of fractional order systems and complex nonlinear systems.

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