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An approach to identification of unknown IIR systems using crossover cat swarm optimization☆

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Summary Traditional learning techniques creates stability problem in infinite impulse response (IIR) systems identification. Additionally the performance significantly degrades if reduced order adaptive models are used for such identification. In this paper identification of IIR system is formulated as an optimization problem. This paper also proposes a modification to the cat swarm optimization algorithm i.e. crossover cat swarm optimization which always tries to explore the search space for improved solutions without getting trapped in the local optima and diverse situations. The results of actual and reduced order identification for standard system by new method exhibit superior performance as compared to cat swarm optimization and particle swarm optimization in terms of mean square error, convergence speed and estimation of coefficients.

Introduction

The IIR filters design is referred as a challenging optimisation problem and mostly plays a role in signal processing and communication. IIR filters use finite number of parameters to generate an infinite impulse response. For a particular level of performance, the number of coefficients involved in IIR filter is less as compared to FIR filter. So the IIR filters are generally used in system identification. The problems associated with design of IIR filter are concept of stability, non-quadratic and multimodal error surface and

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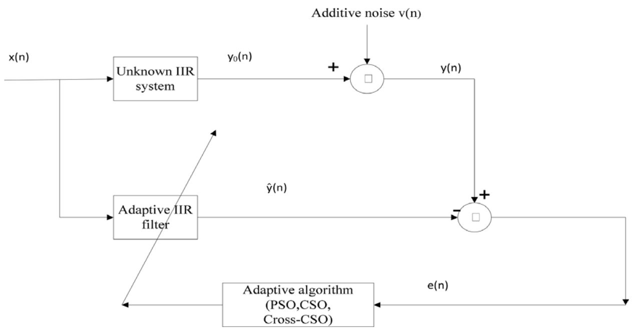

Figure 1 Block diagram of System Identification with various adaptive algorithms.

slow convergence. So, monitoring the stability of higher order IIR filter is very essential during learning process. The behaviour of IIR algorithm offers difficult prediction as IIR filter with adaptive nature have more complex properties than a similar type FIR filter.

System identification

System identification is the process of optimizing adaptive filter coefficients to match with unknown plant (Fig. 1).

The transfer function (Panda et al., 2011) of unknown system can be specified as $H_p(z) = \left[\frac{A(z)}{B(z)}\right]$

The $A(z)$ and $B(z)$ can be described as $A(z) = \sum_{i=0}^{L} a_i z^{-i} \quad B(z) = 1 - \sum_{i=0}^{M} b_i z^{-i}$

Generally, filter order M is greater than filter order L. So, difference equation describing the unknown IIR system with the input $x\ (n)$ is specified as $y_0(n) = H_p(z)x(n)$. The output of the plant with the addition of noise is given as

$$y(n) = y_0(n) + v(n)$$

Similarly, transfer function of IIR filter is in same format as unknown system and its output is taken as $\hat{y}(n)$ and error is $e(n) = y(n) - \hat{y}(n)$

So, cost function for unknown system identification is formulated for optimisation as $J = E[e^2(n)] \approx \frac{1}{N}\sum_{n=1}^{N} e^2(n)$

Cat swarm optimization

Chu and Tsai (2007) has been proposed a new algorithm namely cat swarm optimization in 2007. In this algorithm the nature of cats for modelling has two modes: 'Seeking mode' and 'Tracing mode. In CSO, the no. of cats are used as particles for solving the problems. In this case, each cat is assigned a position consists of D dimensions with velocities for each dimension. The best position obtained by one of cats is final solution. Essential Parameters for seeking mode are SMP, SRD, CDC and SPC (Chu and Tsai, 2007; Panda et al., 2011). Tracing mode provides a local search technique for optimization problem. The update equations for position and velocity with each iteration with w, c as inertia weight, acceleration constant respectively and r is a random number uniformly distributed within range [0,1] are given by:

$$V_{id} = w * V_{id} + c * r * (P_{gd} - X_{id}) \quad X_{id} = X_{id} + V_{id}$$

Proposed crossover cat swarm optimization

To achieve better exploration of the search space with higher accuracy, we propose an improved CSO algorithm. The cats present in tracing mode are separated into parent 1 and parent 2. By using crossover mechanism of GA (Gen and Cheng, 1997) new offspring are generated. The offspring and the parent are mixed .Then fitness of all the cats are evaluated and best position is stored.

Steps of the Algorithm

- Generate random population of cats having initial position and velocities. The dimensions of the cats must be same as weights of IIR filter.
- Evaluate fitness of cats to store best position as $P_{g.}$
- According to MR, the cats go for tracing mode and according to SMP; the cats go for seeking mode. The indices of position matrix in tracing mode are given by $q = 1, 2, \ldots, L/(1 + \mathrm{MR})$, where L is population size.
- Evaluate the fitness of cats in seeking mode and store best position.
- Divide cats in tracing mode into parent 1 and parent 2 cats and apply uniform crossover to produce child.
- Then mix child cats and parent cats and calculate fitness values and store best position as P_{lm}.
- Update P_g by comparing fitness of P_g and P_{lm}.
- Check termination conditions and if they do not satisfy then repeat steps 3—7.

Results and discussions

The modelling of unknown plant for system identification is done by using a filter of same order as that of plant or a filter of reduced order. The results include both actual and reduced order convergence characteristics of PSO (Kennedy and Eberhart, 1995), CSO, Cross-CSO and the MSE for an IIR plant. Results also include the estimated and actual parameters. The standard transfer function of fourth order plant is (Panda et al., 2011; Shynk, 1989a,b). The simulation parameter are SMP = 5, CDC = 80%, MR = 0.9 and SRD = 20%.

Table 1 Parameter estimation for 4th order system modelled with 4th order filter.

Parameters	Actual value	PSO	CSO	Cross-CSO
a_1	−0.9000	−0.8501	−0.9439	−0.9345
a_2	0.8100	0.8843	0.8097	0.8054
a_3	−0.7290	−0.7469	−0.7181	−0.7252
b_1	−0.0400	−0.0220	−0.0475	−0.0428
b_2	−0.2775	−0.2056	−0.2202	−0.2764
b_3	0.2101	0.2146	0.2139	0.2076
b_4	−0.1400	−0.1972	−0.1587	−0.1395

Table 2 MSE of 4th order system with a 4th order filter and with 3rd order filter.

MSE	4th Order system with 4th order filter			4th Order system with 3rd order filter		
	PSO	CSO	Cross-CSO	PSO	CSO	Cross-CSO
Best	1.2108×10^{-5}	2.4506×10^{-8}	4.0738×10^{-11}	7.1134×10^{-5}	2.1646×10^{-7}	2.0121×10^{-9}
Worst	3.6607×10^{-3}	9.9853×10^{-6}	3.3113×10^{-9}	9.0157×10^{-3}	9.0232×10^{-5}	5.0183×10^{-7}
Average	1.5857×10^{-4}	3.3624×10^{-7}	2.8407×10^{-10}	6.8855×10^{-4}	7.0255×10^{-6}	2.6069×10^{-8}

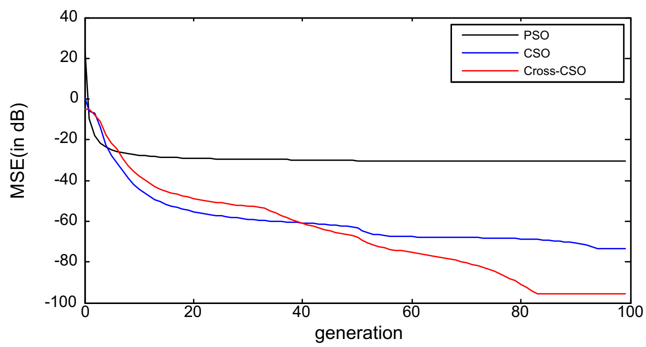

Figure 2 Convergence for 4th order system and 4th order filter.

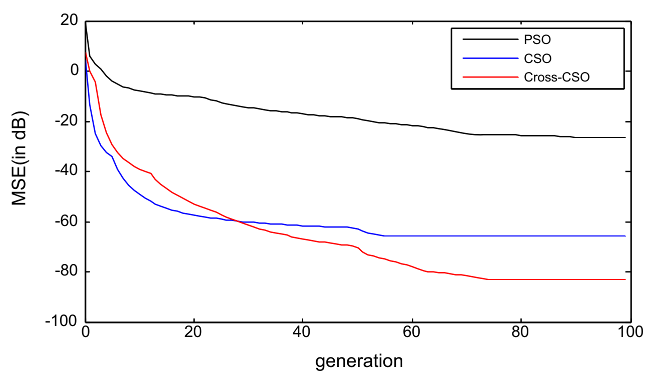

Figure 3 Convergence for 4th order system and 3rd order filter.

$$H_S(z) = \left[\frac{1 - 0.9z^{-1} + 0.81z^{-2} - 0.729z^{-3}}{1 + 0.04z^{-1} + 0.2775z^{-2} - 0.2101z^{-3} + 0.14z^{-4}}\right]$$

So, the transfer function of filter is $H_S(z) = \left[\frac{a_0 + a_1z^{-1} + a_2z^{-2} + a_3z^{-3}}{1 - b_1z^{-1} - b_2z^{-2} - b_3z^{-3} - b_4z^{-4}}\right]$

The Table 1 shows parameter estimation of Cross-CSO algorithm which is better as compared to PSO and CSO algorithm. The Table 2 clearly indicates quantitative performance of proposed algorithm for several numbers of runs. Figs. 2 and 3 show performance of three algorithms among which Cross-CSO is best. In Fig. 2, PSO converge to a value of −30.58 dB at 63 iterations whereas CSO converge to −73.66 dB at 95 iterations. But among all Cross-CSO converge to −95.38 dB at only 84 iterations. Cross-CSO algorithm also provides better MSE as compared to PSO and CSO algorithm for multimodal problem. But the time taken by Cross-CSO is higher as compared PSO and CSO. The extra time taken by Cross-CSO is due to enhancement of global search by generation of more number of cats by crossover operation.

Conclusion

This paper proposed a modification to CSO algorithm i.e. Cross-CSO algorithm for exploration of the search space towards global finest solutions and to avoid the difficulties like local trapping and diverged situations. After comparing with PSO and CSO, it can be concluded that Cross-CSO gave the best results in terms of MSE and estimation of coefficients. Also it performed well when used by identification with reduced order filter. However, the computation time of the proposed algorithm is higher than of PSO and CSO. But, this affordable higher computational time can be easily conciliated through better performance.

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