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Research Paper

Application of Slime Mould Algorithm to Infinite Impulse Response System Identification Problem

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Abstract—Recently, the researchers working in the field of science and engineering have paid a considerable attention to the concept of the system identification to tackle with complex optimization problems. It is feasible to achieve more accurate models of physical plants with the infinite impulse response (IIR) models compared to their finite counterparts (FIR). To get the most out of the IIR models for the system identification, metaheuristic optimization algorithms can be used as efficient solutions. This work, therefore, aims to demonstrate more promising performance of a new metaheuristic algorithm named slime mould algorithm. In this regard, a comparative assessment is performed using different metaheuristic optimization techniques and different IIR model identification problems are considered. The slime mould algorithm is shown to achieve better accuracy and robustness in terms of IIR model identification with the help of obtained statistical results.

Keywords: *IIR adaptive filter, System identification, Slime mould algorithm, Metaheuristic algorithms*.

1. Introduction

It is feasible to observe the appetite of the researchers towards one of the complex optimization problems known as system identification. Such an appetite is due to the significant role of the system identification in different fields of science and engineering (Mohammadi et al., 2019). To obtain an optimal model for the unknown plant, an optimizer is used in system identification which minimizes an error function (Zhao et al., 2020). Performing an effective minimization on the error function would help to achieve an optimal model.

Since the infinite impulse response (IIR) models are able to mimic the physical plants more accurately compared to finite impulse response (FIR) models and only require fewer parameters to meet the performance specifications, they are widely used for the purpose of the system identification (Kumar et al., 2016). The metaheuristic optimizers have recently been used as promising candidates to deal with IIR modeling since such optimizers have so far shown to reach more accurate and robust results (Eswari et al., 2021). Therefore, different metaheuristic algorithm examples such as cat swarm optimization (Panda et al., 2011), harmony search algorithm (Saha et al., 2014), bat algorithm (Kumar et al., 2016), selfish herd optimization (Zhao et al., 2020) and average differential evolution algorithm (Durmuş, 2022) can be found in the literature for IIR system identification.

In the light of the aforementioned capability of the metaheuristic optimizers, this study aims to further demonstrate the promise another recent metaheuristic algorithm for IIR system identification such that more accurate and robust results can be reached. Therefore, in this work, the promise of the slime mould algorithm (Li et al., 2020) is comparatively presented for IIR model identification. We have employed the latter optimizer as it has already been demonstrated to be a competitive candidate for several different problems such as optimizing the parameters of power system stabilizer (Ekinci et al., 2020), designing PID (Izci & Ekinci, 2021) and FOPID (Izci, Ekinci, Zeynelgil, et al., 2021) controllers, extracting optimal model parameters of the photovoltaic panel (Mostafa et al., 2020), monitoring structural health (Tiachacht et al., 2021), designing controller for magnetic levitation system (Izci, Ekinci, Eker, et al., 2021), cost-effective solution for economic load dispatch problem (Kamboj et al., 2022) and optimizing functions (Izci, 2021).

To demonstrate the performance of the slime mould algorithm reaching more accurate and robust results, three different cases of the IIR system examples (second-order plant with a first order IIR model, second-order plant with a second order IIR model and high-order plant with a high-order IIR model) were considered in this study. Then, the available metaheuristic optimizers-based studies of flower pollination algorithm, cuckoo search algorithm, electromagnetism-like algorithm, artificial bee colony algorithm and particle swarm optimization algorithm (Cuevas et al., 2014) were employed for comparisons. The comparative examinations confirmed that the slime mould algorithm can reach more promising performance for the IIR model identification.

2. Slime Mould Algorithm

The slime mould algorithm (SMA) employs the foraging behavior of Physarum Polycephalum (Li et al., 2020) in order to mathematically describe a stochastic optimizer. The first step of the SMA algorithm is the initialization stage which mimics the behavior of the approaching food. The following model is used in this step where $\vec{X}$ is the location of the slime mould and $\overrightarrow{X_b}$ is the current location with the highest odor concentration.

$$\overrightarrow{X(t+1)} = \begin{cases} \overrightarrow{X_b(t)} + \overrightarrow{vb} \cdot \left(\vec{W} \cdot \overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}\right), r < p \\ \overrightarrow{vc} \cdot \overrightarrow{X(t)}, r \geq p \end{cases} \tag{1}$$

In here, $\overrightarrow{X_A}$ and $\overrightarrow{X_B}$ stand for individuals that are randomly chosen from slime mould, r represents a random value (range between $[0, 1]$) whereas $\overrightarrow{vc}$ is a parameter decreasing from 1 to 0. $\overrightarrow{vb}$, on the other hand, is a parameter with range $[-a, a]$. The value of a is calculated as:

$$a = arctanh\left(-\left(\frac{t}{t_{max}}\right) + 1\right) \tag{2}$$

where t_{max} is the maximum iteration. The condition of p, given in (1), is defined as:

$$p = tanh|S(i) - DF| \tag{3}$$

where $S(i)$ is the current fitness value ($i \in 1,2, \dots n$) and DF is the best fitness of all iterations. The weight, $\vec{W}$, of slime mould is calculated as follows where $cond$ indicates the first half of the population ranked by $S(i)$.

$$\vec{W}\big(SmellIndex(i)\big) = \begin{cases} 1 + r \cdot \log\left(\frac{bF - S(i)}{bF - wF} + 1\right), cond \\ 1 - r \cdot \log\left(\frac{bF - S(i)}{bF - wF} + 1\right), others \end{cases} \tag{4}$$

In (4), bF and wF respectively stand for the optimal and the worst fitness achieved in the current iteration.

The second step of the SMA algorithm is the updating stage which considers the behavior related to the wrapping food, thus, the contraction mode of slime mould is mathematically simulated. That essentially means slime mould generates a strong wave in case of contracting a high concentration of food through the vein which causes a thick vein and a fast flow of cytoplasm. In case of lower concentrations, the exploration of other regions is performed. Such a behavior can be modeled as follows and used for the location update where $rand$ is a random value ranging between $[0, 1]$, LB is the lower bound and UB is the upper bound of the search space and z is a parameter ranging between $[0, 0.1]$.

$$\overrightarrow{X^*} = \begin{cases} rand \cdot (UB - LB) + LB, rand < z \\ \overrightarrow{X_b(t)} + \overrightarrow{vb} \cdot \left(\vec{W} \cdot \overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}\right), r < p \\ \overrightarrow{vc} \cdot \overrightarrow{X(t)}, r \geq p \end{cases} \tag{5}$$

The last step of the SMA algorithm is related to the oscillation. The slime mould produces a wave to search for the position of the food with better concentration. The slime mould approaches high concentrated food locations quicker. On the other hand, a slower approach is employed to reach lower concentrated food locations. Such behavior increases the efficiency of finding the optimal food location. Figure 1 illustrates the steps of the SMA algorithm.

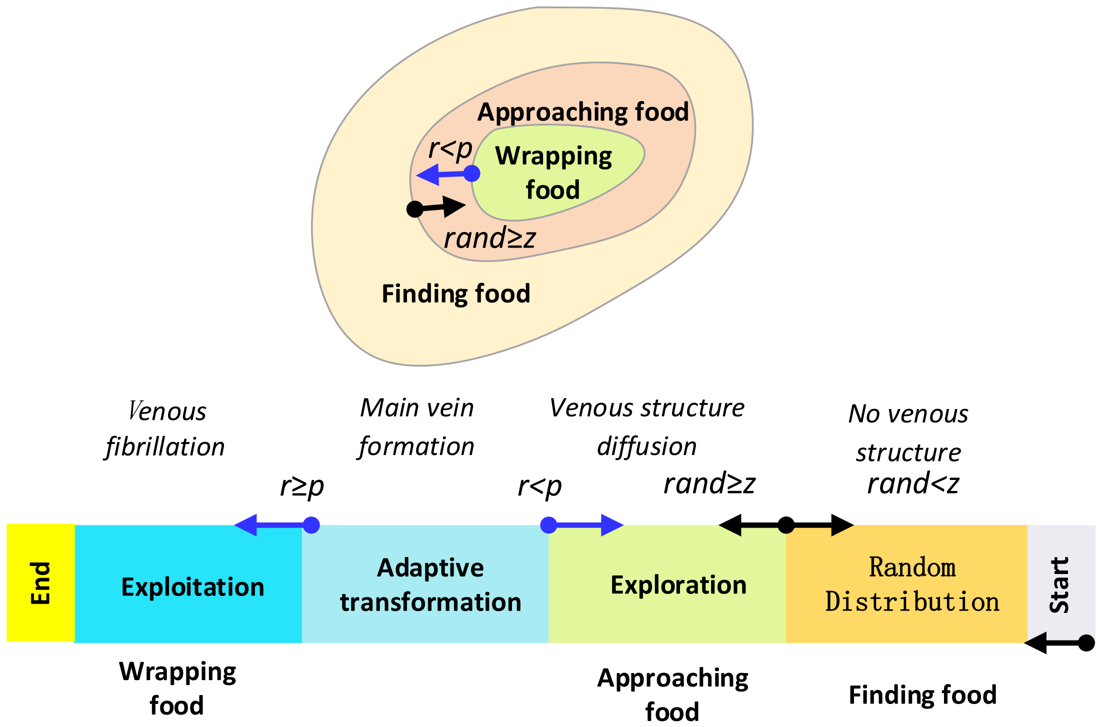

Figure 1. The steps of the slime mould algorithm (Li et al., 2020)

3. Adaptive IIR Filter Model

It is feasible to model the problems encountered in signal processing as a system identification problem, thus, the adaptive IIR filter has so far been widely adopted for this purpose. The appropriate filter coefficients are searched by an adaptive algorithm in IIR filter design so that the output of the respective filter can be as close to an unknown system as possible. Figure 2 demonstrates the block diagram of an adaptive IIR system identification based on the proposed SMA algorithm.

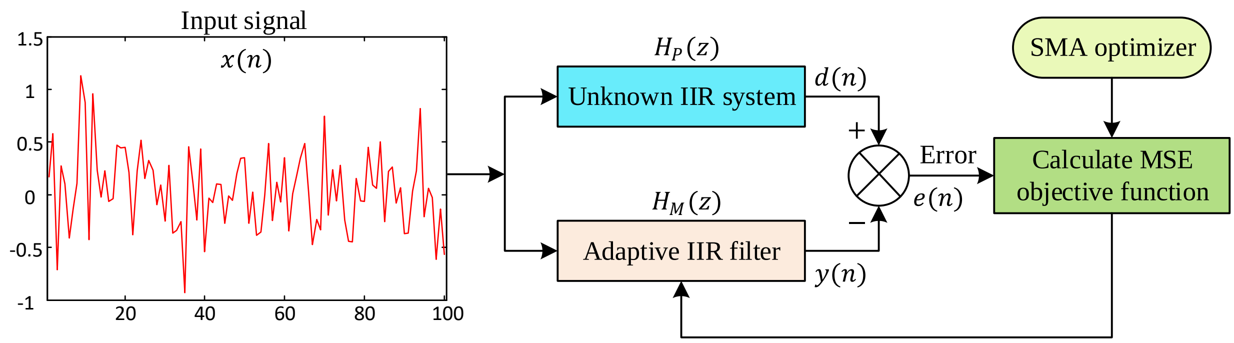

Figure 2. Block diagram of adaptive IIR model designed by the SMA optimizer

The IIR system's input-output relationship can be expressed as follows (Durmuş, 2022; Karaboga, 2009) where the input and the output of the filter are represented by $x(n)$ and $y(n)$, respectively.

$$y(n) + \sum_{i=1}^{M} a_i y(n-i) = \sum_{i=0}^{N} b_i x(n-i) \tag{6}$$

In here, M $(\geq N)$ represents the filter order. The following general form can then be obtained to describe the transfer function of this IIR filter.

$$H(z) = \frac{B(z)}{A(z)} = \frac{\sum_{i=0}^{N} b_i z^{-i}}{1 + \sum_{i=1}^{M} a_i z^{-i}} \tag{7}$$

As shown in Figure 2, the terms of the $H_P(z)$ and $H_M(z)$, in the design method, are respectively representing the transfer functions of the unknown plant and the IIR model. Besides, the desired response of the unknown IIR plant is represented by $d(n)$ whereas $e(n) = d(n) - y(n)$ is the error signal. The main aim of the identification is to describe a cost function ($J(\theta)$), as given below, for minimization where L stands for the number of input samples which are utilized for calculating the respective cost function.

$$J(\theta) = MSE = \frac{1}{L}\sum_{n=1}^{L} e^2(n) \tag{8}$$

The mean square error (MSE) equals to $J(\theta)$ and produces the coefficient vectors of the IIR model. In here, $\theta = [b_0, b_1, \dots, b_N, a_1, a_2, \dots, a_M]^T$. The SMA algorithm in here attempts to minimize the MSE through adjusting coefficient vector θ of transfer function $H_M(z)$.

4. Simulation Results

In this study we considered three different cases to demonstrate the superiority of the SMA algorithm for the IIR model identification. For those cases, the parameters of the SMA algorithm were set as follows:

- z= 0.03,
- number of slime mould colony (population size) = 25,
- maximum iteration number = 3000 and number of runs = 30.

For all simulations, the input signal, $x(n)$, was taken as $L = 100$ samples of Gaussian white noise with zero mean and 0.1 variance (Cuevas et al., 2014). For the comparisons in the considered three cases of the IIR system examples, flower pollination algorithm (FPA) (Cuevas et al., 2014), cuckoo search (CS) algorithm (Cuevas et al., 2014), electromagnetism-like (EM) algorithm (Cuevas et al., 2014), artificial bee colony (ABC) algorithm (Cuevas et al., 2014) and particle swarm optimization (PSO) algorithm (Cuevas et al., 2014) were employed. For the latter algorithms, the population size was taken as 25 and the maximum iteration number was set to 3000.

4.1. Example 1

We initially aimed to identify a second-order plant through a first order IIR model in the first example. For this reason, the following transfer functions are used for the unknown plant (H_P) and the IIR model (H_M).

$$H_P(z) = \frac{0.05 - 0.4z^{-1}}{1 - 1.1314z^{-1} + 0.25z^{-2}} \tag{9}$$

$$H_M(z) = \frac{b_0}{1 - a_1 z^{-1}} \tag{10}$$

For the first example, the obtained best values for the parameters of b_0 and a_1 are reported in Table 1 and the statistical performance assessment for different algorithms are provided in Table 2. As we demonstrate in Table 2, the SMA algorithm outperforms the compared algorithms as it achieves far better results than the algorithms of FPA, CS, EM, ABC and PSO.

Table 1. Optimized parameter values with different algorithms for the first example

Coefficients	Optimized value					
	SMA	FPA (Cuevas et al., 2014)	CS (Cuevas et al., 2014)	EM (Cuevas et al., 2014)	ABC (Cuevas et al., 2014)	PSO (Cuevas et al., 2014)
b_0	−0.2903	−0.2001	−0.2382	0.3030	−0.3525	−0.3012
a_1	0.9203	0.9364	0.9173	0.9034	0.1420	0.9125

Table 2. Obtained statistical values for the first example

Algorithms	MSE	
	Mean	Standard deviation
SMA	9.5657E−03	1.3394E−04
FPA (Cuevas et al., 2014)	0.0105	5.103E−04
CS (Cuevas et al., 2014)	0.0101	3.118E−04
EM (Cuevas et al., 2014)	0.0165	0.0012
ABC (Cuevas et al., 2014)	0.0197	0.0015
PSO (Cuevas et al., 2014)	0.0284	0.0105

4.2. Example 2

In the second example, we attempted to identify a second-order plant through a second-order IIR model. For the second case, the following transfer functions are used for the unknown plant (H_P) and the IIR model (H_M).

$$H_P(z) = \frac{1}{1 - 1.4z^{-1} + 0.49z^{-2}} \tag{11}$$

$$H_M(z) = \frac{b_0}{1 + a_1 z^{-1} + a_2 z^{-2}} \tag{12}$$

For the second example, the obtained best values for the parameters of b_0, a_1 and a_2 are reported in Table 3 and the statistical performance assessment for different algorithms are provided in Table 4. As we demonstrate in Table 4, the SMA algorithm has similar performance as the CS algorithm, however, outperforms the rest of the compared algorithms.

Table 3. Optimized parameter values with different algorithms for the second example

Coefficients	Exact value	Optimized value					
		SMA	FPA (Cuevas et al., 2014)	CS (Cuevas et al., 2014)	EM (Cuevas et al., 2014)	ABC (Cuevas et al., 2014)	PSO (Cuevas et al., 2014)
b_0	1.0000	1.0000	1.0000	1.0000	1.0091	0.2736	0.9706
a_1	−1.4000	−1.4000	−1.4000	−1.4000	−1.0301	−1.2138	−1.4024
a_2	0.4900	0.4900	0.4900	0.4900	0.4802	0.6850	0.4925

Table 4. Obtained statistical values for the second example

Algorithms	MSE	
	Mean	Standard deviation
SMA	0.0000	0.0000
FPA (Cuevas et al., 2014)	4.6246E−32	2.7360E−31
CS (Cuevas et al., 2014)	0.0000	0.0000
EM (Cuevas et al., 2014)	3.9648E−05	8.7077E−05
ABC (Cuevas et al., 2014)	0.3584	0.1987
PSO (Cuevas et al., 2014)	4.0035E−05	1.3970E−05

4.3. Example 3

Lastly, we attempted to identify a higher-order plant through a high-order IIR model. For the third case, the following transfer functions are used for the unknown plant (H_P) and the IIR model (H_M).

$$H_P(z) = \frac{1 - 0.4z^{-2} - 0.65z^{-4} + 0.26z^{-6}}{1 - 0.77z^{-2} - 0.8498z^{-4} + 0.6486z^{-6}} \tag{13}$$

$$H_M(z) = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2} + b_3 z^{-3} + b_4 z^{-4}}{1 + a_1 z^{-1} + a_2 z^{-2} + a_3 z^{-3} + a_4 z^{-4}} \tag{14}$$

For the last example, the obtained best values for the parameters of b_0, b_1, b_2, b_3, b_4, a_1, a_2, a_3 and a_4 are reported in Table 5 and the statistical performance assessment for different algorithms are provided in Table 6. As we demonstrate in Table 6, the SMA algorithm outperforms all the compared algorithms.

Table 5. Optimized parameter values with different algorithms for the third example

Coefficients	Optimized value					
	SMA	FPA (Cuevas et al., 2014)	CS (Cuevas et al., 2014)	EM (Cuevas et al., 2014)	ABC (Cuevas et al., 2014)	PSO (Cuevas et al., 2014)
b_0	0.9945	1.0171	−0.2377	1.0335	0.5214	0.9939
b_1	−0.0206	0.0038	0.0031	−0.6670	−1.2703	−0.6601
b_2	0.3649	0.2374	−0.3579	−0.4682	0.3520	−0.8520
b_3	−0.0080	0.0259	0.0011	0.6961	1.1816	0.2275
b_4	−0.3657	−0.3365	−0.5330	−0.0673	−1.9411	−1.4990
a_1	−0.0115	0.0328	0.9599	−0.4950	−1.1634	0.3683
a_2	0.0023	−0.1059	0.0248	−0.7049	−0.6354	−0.7043
a_3	0.0018	−0.0243	0.0368	0.5656	−1.5182	0.2807
a_4	−0.8522	−0.7619	−0.0002	−0.2691	0.6923	0.3818

Table 6. Obtained statistical values for the third example

Algorithms	MSE	
	Mean	Standard deviation
SMA	4.9076E−05	8.5898E−07
FPA (Cuevas et al., 2014)	0.0018	0.0020
CS (Cuevas et al., 2014)	6.7515E−04	4.1451E−04
EM (Cuevas et al., 2014)	0.0140	0.0064
ABC (Cuevas et al., 2014)	7.3067	4.3194
PSO (Cuevas et al., 2014)	5.8843	3.4812

5. Conclusion

In this work, we have presented the promise of the SMA optimizer for the IIR model identification using comparative assessments. To do so, we have utilized the identification task as an optimization problem. To demonstrate the promise, we have employed three distinct cases (second-order plant with a first-order IIR model, second-order plant with a second-order IIR model and high-order plant with a high-order IIR model) as problems with different difficulties. Different metaheuristic optimizers (FPA, CS, EM, ABC and PSO) then employed for performing comparative assessments. The obtained results have confirmed the highly competitive performance of the SMA optimizer reaching better accuracy and robustness for the IIR model identification.

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