Parameter Estimation Using a SCE Strategy

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Abstract. As a novel evolutionary computation technique, shuffled complex evolution (SCE) has attracted much attention and wide applications for solving complex optimization problems in different fields. This paper utilizes SCE strategy to estimate parameters of structural systems, which could be formulated as a multi-modal optimization problem with high dimension. Simulation results for identifying the parameters of a structural system under four conditions including limited output data, noise polluted signals, and no prior knowledge of mass, damping, or stiffness are presented to demonstrate the effectiveness of the proposed method.

1 Introduction

In system identification, considerable efforts have been invested in developing methods for identification of system models and their parameters. For civil-engineering systems, limited progress has been made with analytical methods for complexity and incomplete prior information. Instead, some successes have been achieved with various intelligent optimization algorithms. Evolution strategy (ES) algorithms have been presented for the identification of multiple degree of freedom (DOF) systems [1]. Perry et al. [2] have presented a modified GA to identify structural systems.

As a novel evolutionary computation technique, Shuffled complex evolution (SCE) has attracted much attention and wide applications, owing to exactness of solution, easy implementation and quick convergence [3].

The SCE method is based on a synthesis of four concepts that have proved successful for global optimization: (a) combination of probabilistic and deterministic approaches; (b) clustering; (c) systematic evolution of a complex of points spanning the space, in the direction of global improvement; and (d) competitive evolution.

In the field of structural engineering, especially system identification, SCE still has not been applied widely. Meanwhile, although numerous traditional approaches in literature tackled the problem of system identification in the field of civil engineering, it is still difficult for these approaches to extract the physical characteristics of the system like mass, damping, or stiffness in a structural system unless some of these are assumed known a priori. Besides, the measurements of inputs and outputs from a real structural system tend to be complex and expensive. Therefore, there is a significant interest in the development of an algorithm that uses as few measurements as possible to obtain the physical characteristics of the system without a priori knowledge of this system.

In this study, a parameter estimation technique based on SCE is presented to overcome some of the difficulties encountered in the field, which could be formulated as

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multimodal numerical optimization problems with high dimension. Four numerical examples are presented from which the effectiveness and efficiency of the SCE are investigated. The influence of incomplete availability of measurements on the performance of SCE for system identification is also discussed.

2 Problem Formulation

The basic idea in system identification is to compare the time dependent response of the system and a parameterized model by a norm or some performance criterion giving a measure to how well the model response fits the system response. Hence, the objective is to find a set of parameters that minimize the prediction error between system output *y(t)* , i.e., the measured data, and model output $\hat{y}(\theta,t)$ at each time-step *t*.

Therefore, our interest lies in minimizing the predefined error norm of the outputs, e.g., the following mean square error (MSE) function.

$$F(\theta)=\frac{1}{T}\sum_{k=1}^{T}\left\|y(k)-\hat{y}(k)\right\|^{2} . \tag{1}$$

where $\|\ \|$ represents the Euclidean norm of vectors. Formally, the optimization problem requires finding a vector $\theta \in R_n$, so that a certain quality criterion is satisfied, namely that the error norm $F(\theta)$ is minimized. The function $F(\theta)$ is commonly called a fitness function or objective function. In SCE, typically an objective function is used which reflects the goodness of solution. The identification problem thus is treated as a linearly constrained multi-dimensional optimization problem, namely

$$\begin{gathered}\min F(\theta), \theta=(\theta_1,\theta_2,\ldots\theta_n)^T . \\ s.t. \theta\in S,\ \ S=\{\theta_{\min i}\le\theta_i\le\theta_{\max i};\ \ \forall i=1,2,\ldots,n\} .\end{gathered} \tag{2}$$

where $F(\theta)$=objective function which maps decision variable θ into the objective space $F=R_n\rightarrow R$, S is the *n*-dimensional feasible search space, $\theta_{\max}$ and $\theta_{\min}$ denote the upper bounds and the lower bounds of the *n* parameters respectively.

3 Shuffled Complex Evolution Algorithm

In SCE, a population of NP (population size) solution vectors is initialized randomly at the start, which is evolved to find optimal solutions through the reflection, hongmutation, contraction, shuffling and selecting operation procedures. An optimization task consisting of *n* parameters can be represented by an *n*-dimensional vector. Let $S\in R_n$ be the search space of the problem under consideration. Then, the SCE algorithm utilizes NP, n-dimensional vectors

$$x_i=(x_{i1},x_{i2},\ldots,x_{in})^T\in\theta,\ \ i=1,2,\ldots,s . \tag{3}$$

as a population for each iteration, called a generation of the algorithm[4].

3.1 Implementation of SCE

The philosophy behind the SCE approach is to treat the global search as a process of natural evolution. The sampled points (s in number) constitute a population. The population is partitioned into several communities (complexes), each of which is permitted to evolve independently (i.e., search the space in different directions). After a certain number of generations, the communities are forced to mix, and new communities are formed through a process of shuffling. This procedure enhances survivability by a sharing of the information (about the search space) gained independently by each community.

3.2 CCE Strategy

Competitive complex evolution (CCE) strategy is the critical part of SCE algorithm. In CCE each member of a community (complex) is a potential parent with the ability to participate in a process of reproduction. A subcomplex selected from the complex is like a pair of parents, except that a subcomplex may consist of more than two members.

To ensure that the evolution process is competitive, the probability that better parents contribute to the generation of offspring is higher than that of worse parents. The use of a triangular probability distribution ensures this competitiveness.

Nelder and Mead's [8] procedure is applied to each subcomplex to generate most of the offspring. CCE uses the information contained in the subcomplex to direct the evolution in an improvement direction.

In addition, offspring are introduced at random locations of the feasible space under certain conditions in order to ensure that the process of evolution does not get trapped by unpromising regions. This is somewhat analogous to mutation in response to stress that can occur in biological evolution. Each mutation also helps to increase the amount of information stored in the sample.

Finally, each new offspring replaces the worst point of the current subcomplex, rather than the worst point of the entire population. This ensures that every parent gets at least one chance to contribute to the reproduction process before being replaced or discarded. Thus, none of the information contained in the sample is ignored.

3.3 Operational Parameters

According to the study result conducted by Duan [7], the SCE2 procedure is on the average the best algorithm. In most problems, it performs better than the SCE1, the other version of SCE. Thus, following Duan’s suggestion, the several key parameters are set the same as the SCE2, where $m=(2n+1)$□$q=n+1$□$x=1$□$y=2n+1$. m = the number of points in each complex, q=the number of points in each subcomplex, x=the number of generations that each subcomplex competitive evolution will take and y=the number of calculation times of each complex’s evolution. As the result, p, which is the number of complexes, becomes the only parameter that requires user specified according to the difficulty of certain problem. When p is relatively large, SCE is able to solve higher dimensional parameter estimation problem; however, at the same time, the method might become computationally demanding as well. Therefore, in this paper p is set to 4.

4 Illustrative Examples

In this paper the problem is made to the most difficult case of unknown mass systems, where the mass, stiffness and damping of the structure are to be identified.

In order to assess the effectiveness of the parameter estimation technique with the SCE presented above, numerical simulations of five degrees of freedom (DOFs) structure system are carried out. The properties of the structural systems are given in Table 1. It is assumed that the system is excited by known forces and that the response of the structure, in terms of accelerations, is recorded at some given points.

Table 1. 5 DOF System Parameters

Stiffness (kN/m)	
Level 1	2.485e5
Level 2	1.921e5
Level 3-5	1.522e5
Mass (kg)	
Level 1-2	2.762e3
Level 3-5	2.300e3
Damping (kN.s/m)	
Level 1	3.129e3
Level 2	2.536e3
Level 3-5	2.030e3

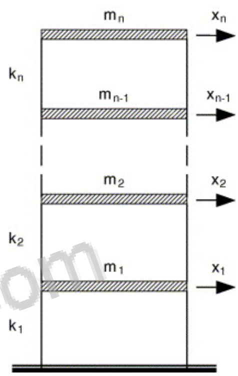

Fig. 1. n-DOF structural system

The dynamic equation of motion of a structural system can be written as

$$M\ddot{x} + C\dot{x} + Kx = u(t) \ . \quad (4)$$

where M, C and K are the mass ($m_1,\ldots,m_5$), damping($c_1,\ldots,c_5$) and stiffness ($k_1,\ldots,k_5$) matrices, x is the displacement vector and u is the input force vector.

Therefore, the system is fully described by the set of parameters

$$\theta = (m_1, m_2, \ldots, m_5;\ k_1, k_2, \ldots, k_5;\ c_1, c_2, \ldots, c_5) \ . \quad (5)$$

The influence of limited availability of measurements on the performance of SCE for parameters estimation is discussed. In the "full output" scenario, measurements at all DOFs are available, whereas in the second "partial output" scenario, only DOFs 2, 4, and 5 are available. The following cases of data availability will be treated here as:

1: Full set of the accelerations (outputs) available

$$y(t) = (\ddot{x}_1(t),\ \ddot{x}_2(t),\ \ldots,\ \ddot{x}_5(t)) \ . \quad (6)$$

2: Partial set of the outputs available

$$y(t) = (\ddot{x}_2(t),\ \ddot{x}_4(t),\ \ddot{x}_5(t)) \ . \quad (7)$$

The statistical simulation results of 5 independent runs for the known mass system with the usage of the SCE strategy and DE algorithm are carried out. The input and output (I/O) data are polluted (in the cases considering noise) with Gaussian, zero mean, white noise sequences, whose root mean-square (RMS) value is adjusted to be a certain percentage of the unpolluted time histories. The mean results of the parametric identification for full output scenario are summarized with 0% and 10% RMS noises.

In these scenarios, the mass distribution of the structure is supposed to be unknown priori. The time records used span a total length of 20 s with a sample time of 0.02 s. The SCE strategy parameter is p=4 and maximum number of function evaluation=20000. The search space is taken as 0.5–2.0 times the exact values.

All identified average results' errors are presented in Table 2. In addition, a typical SCE search performance for the 10% noise with partial measurements scenario is provided in Fig. 2, and a typical convergence characteristic of estimation for 4 scenarios is shown in Fig. 3. The following four scenarios tested includes:

CASE1: 0% noise + Full Outputs
CASE2: 0% noise + Partial Outputs
CASE3: 10% noise + Full Outputs
CASE4: 10% noise + Partial Outputs

Table 2. Results' errors for 4 cases

Par		CASE1		CASE2		CASE3		CASE4	
		SCE	DE	SCE	DE	SCE	DE	SCE	DE
m_1~m_5	Min err	0.01	0.00	0.02	0.02	0.04	0.07	0.01	0.06
	Max err	0.03	0.09	0.21	0.16	0.37	0.31	0.29	0.52
	Mean err	0.02	0.04	0.11	0.07	0.27	0.18	0.14	0.29
k_1~k_5	Min err	0.00	0.01	0.00	0.06	0.23	0.04	0.05	0.13
	Max err	0.04	0.09	0.12	0.49	0.42	0.29	0.70	0.68
	Mean err	0.02	0.05	0.06	0.29	0.30	0.14	0.34	0.36
c_1~c_5	Min err	0.42	0.11	1.58	0.73	0.24	0.03	0.96	2.13
	Max err	0.12	0.97	4.66	2.56	2.74	2.58	6.52	7.82
	Mean err	0.26	0.70	3.00	1.75	1.01	1.28	3.82	3.45

Note: Relative errors of identification are in parentheses expressed in %.

From Table 2, without noise disturbing, it can be seen that the results obtained by both SCE and the DE are very close to the true values. The average results and errors obtained by DE a little outperform those obtained by the SCE. With 10% noise polluted, the values of estimated parameters obtained by SCE and DE are still very close to the true values of original parameters. These two schemes both seem to be powerful in escaping local optima and in search for the global optimum on complex problems.

From Figs. 2-3, we observe that for the cases without noise, in the first 50 generations, the convergences of estimation by SCE are faster than DE, but in the second 50 generations the DE outperforms the SCE. In the cases with 10% results, it is obvious that the SCE algorithms can get the true values much more quickly.

The results show that the SCE seems to perform well to the structural system identification problem, especially the polluted cases, yielding very accurate results but

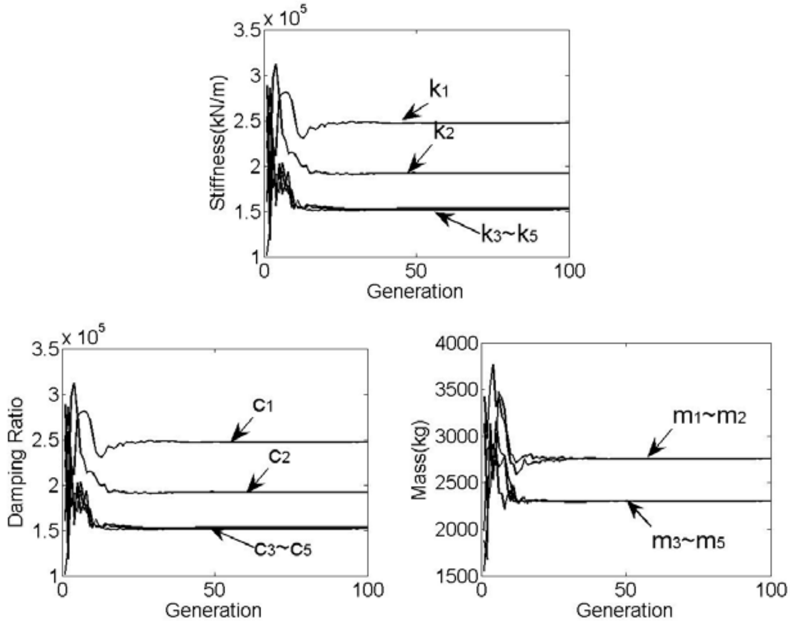

Fig. 2. Typical identification results for 5-DOF unknown mass system (partial measurement with 10% noise) by SCE

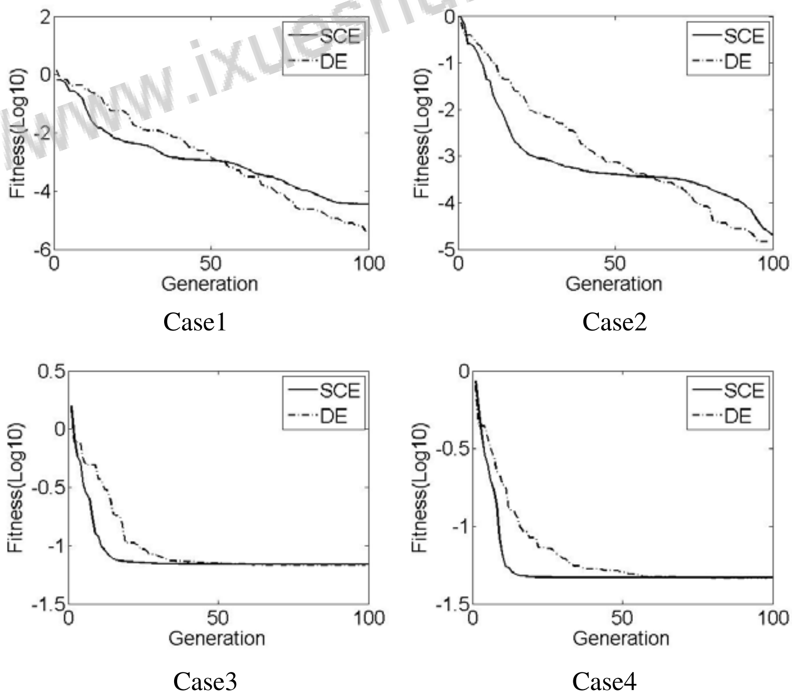

Fig. 3. One typical convergence characteristic of estimation for 4 scenarios

requiring less computing effort. The largest relative errors are usually observed in the damping coefficients. Due to the fact that the damping parameter has only a small contribution to the overall response, its value is generally poorly estimated. This is a fact that has been reported in other studies [1][2] as well.

In addition, the SCE approach is capable of locating the global optimum in all runs with in rather good results errors. It is well known that unknown mass systems are highly multimodal problems. Nevertheless, the maximum error of SCE is very good in damping of only 6.52% with partial output under 10% noise polluted in which DE reaches to 7.82%.

5 Conclusion

This paper has presented a shuffled complex evolution (SCE) strategy for the problem of structural system identification. SCE is very easy to implement and requires only one parameter tuning. Four numeric experiments have been conducted to assess the applicability of the SCE for structural parameters estimation. The results from our study show that SCE clearly and consistently performs excellent for hard unknown mass problems, both in respect to precision as well as robustness of the results. This proposed approach has no special requirements regarding the incomplete output measurements from the system. Even when the mass, stiffness and damping of the structure are unknown, the SCE can still converge to accurate results. The SCE approach is a promising tool for parameters estimation of structural systems in the sense that it is an optimal method requiring no prior knowledge on the structure.

Acknowledgments

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