Parameter Estimation in Five Dimensions Chaotic Synchronization Systems by Self-Organizing Migrating Algorithm

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Abstract: - This paper aims to present the combination of chaotic signal and evolutionary algorithm to estimate the unknown parameters in five-dimension chaos synchronization system via the Pecora-Carroll method. The self-organizing migrating algorithm was used to estimate the unknown parameters. Based on the results from evolutionary algorithm, two identical chaotic systems were synchronized.

Key-Words: - Secure communication, 5D chaotic system, identical synchronization, self-organizing migrating algorithm, Pecora-Carroll method.

1 Introduction

Chaos theory is one of the most important achievements in nonlinear system research. Chaos dynamics are deterministic but extremely sensitive to initial conditions. Chaos has attracted great interests from researchers of different fields including economics [1], engineering [2], etc. Chaotic systems and their applications in secure communications have received a great deal of attention since Pecora and Carroll proposed a method to synchronize two identical chaotic systems under different initial conditions [3]. The high unpredictability of chaotic signal is the most attractive feature of chaos based secure communication. Several types of synchronization have been considered in communication systems, such as Pecora and Carroll (PC) method [3], Ott, Grebogi and Yorke (OGY) method [4], feedback approach [5], adaptive method [6], time-delay feedback approach [7], back-stepping design technique [8], etc. In practice, some or all of the system's parameters are unknown. So that, many of proposed solutions focused on synchronization-based on the methods of parameter estimation [13]-[23]. In [22], [23], the parameters of a given dynamic model were estimated by minimizing the average synchronization error using a scalar time series, etc. However, most researches about chaos synchronization concern the synchronization of low dimensional systems. Recently, Roy and Musielak presented a five-dimensional system by adding two additional variables into the three-dimensional Lorenz system [10]. Basic properties of the five-dimensional system have been analyzed by means of the Lyapunov exponents and bifurcation diagrams. Their study shows that the system could generate various complex chaotic attractors when the system parameters were changed.

A new class of stochastic optimization algorithm called self-organizing migrating algorithm (SOMA) was proposed in literature [25], [26]. SOMA works on a population of potential solutions called specimen and it is based on the self-organizing behavior of groups of individuals in a "social environment". It was demonstrated that SOMA has ability to escape the traps in local optimal and easily to achieve the global optimal. Therefore, SOMA has attracted much attentions and wide applications in different fields mainly in various continuous optimization problems.

The higher dimensional systems have the more initial conditions, so they will be more complex than the lower dimension systems. The secure of communication system is increasing with the higher unpredictability of chaotic system, it also more difficult to estimate the unknown parameters.

Motivated by the aforementioned studies, this paper aims to present the combination of chaotic signal with self-organizing migrating algorithm to estimate the unknown parameters in 5D chaotic synchronization system via Pecora and Carroll method under different initial conditions. Based on the results of self-organizing migrating algorithm, the estimated parameters were used to synchronize two 5- dimension chaotic systems.

2 Problem Formulation

2.1 Pecora-Carroll method

In 1989, Pecora and Carroll introduced a method for constructing synchronizing chaotic systems [3], which was used by X. Liao, G Chen and O. Wang in [19]. They showed that when a state variable from a chaotic system was input into a replica subsystem of the original one, both systems could be synchronized identically. They decomposed the dynamical system

$$\dot{\mathbf{u}} = \mathbf{g}(\mathbf{u}) \tag{1}$$

into two subsystems,

$$\begin{aligned} \dot{\mathbf{v}} &= \mathbf{g}_{\mathrm{v}}(\mathbf{v}, \mathbf{w}) \\ \dot{\mathbf{w}} &= \mathbf{g}_{\mathrm{w}}(\mathbf{v}, \mathbf{w}) \end{aligned} \tag{2}$$

with $\mathbf{v = (u_1, \dots , u_k)}$ and $\mathbf{w = (u_{k+1}, \dots , u_n)}$.

and considered one of the decomposed subsystems as the driving signal, say **v**, to be injected into the response system,

$$\dot{\mathbf{w}}' = \mathbf{g}_{\mathrm{w}}(\mathbf{v}, \mathbf{w}') \tag{3}$$

that was given by the same vector field $\mathbf{g_w}$, the same driving **v**, but different variables **w´** synchronizes with the original w subsystem.

Consider the difference of these two systems **e = w´ – w**. The synchronization of the pair of identical systems (2) and (3) occurs if the dynamical system describing the evolution of the difference $|\boldsymbol{w}' - \boldsymbol{w}| \to 0$ as $\boldsymbol{t} \to \infty$.

2.2 The parameter estimation

When estimating the parameters, suppose that the structure of the system is known in advance, the transmitter (driver) system is set with original parameters and the parameter in receiver (response) system is unknown. Therefore, the problem of parameter estimation can be formulated as the following optimization problem:

$$\mathrm{CF} = \sqrt{\frac{1}{M}\sum_{t=1}^{M} |w'_t - w_t|^2} \tag{4}$$

where M denotes length of data used for parameter estimation, the parameter can be estimated by minimum the cost function CF(4).

Because of the irregular dynamic behavior of chaotic systems, the parameter estimation of chaotic systems is a multidimensional continuous optimization problem, the parameters are not easy to obtain. In addition, there are often multiple variables in the problem and multiple local optimums in the landscape of cost function, so traditional optimization methods are easy to trap in local optima and difficult to achieve the global optimal parameters. Therefore, SOMA was chosen because it has been demonstrated that the algorithm has the ability to converge toward the global optimum.

3 Self - Organizing Migrating Algorithm

Self-Organizing Migration Algorithm (SOMA) - one of the evolutionary algorithms was chosen. It imitates nature process of wildlife migration. The method was established in 1999 and developed by Prof. Ivan Zelinka at the University of Tomas Bata, Zlín. SOMA is a stochastic optimization algorithm that is modeled on the social behavior of cooperating individuals [25]. The approach is similar to that of genetic algorithms (GA), although it is based on the idea of a series of “migrations” by a fixed set of individuals, rather than the development of successive generations. It can be applied to any cost-minimization problem with a bounded parameter space, and robust to local minima. SOMA works on a population of candidate solutions in loops called migration loops. The population is initialized randomly distributed over the search space at the beginning of the search. In each loop, the population is evaluated and the solution with the highest fitness becomes the leader ‘L’. Apart from the leader, in one migration loop, all individuals will traverse the input space in the direction of the leader. Mutation, the random perturbation of individuals, is an important operation for evolutionary strategies (ES). It ensures the diversity amongst the individuals and also provides the means to restore lost information in a population. Mutation is different in SOMA compared with other ES strategies. SOMA uses a parameter called perturbation of migration (PRT) to achieve perturbation. This parameter has the same effect for SOMA as mutation has for GA.

The novelty of this approach is that the PRT vector is created before an individual starts its journey over the search space. The PRT vector defines the final movement of an active individual in search space.

The randomly generated binary perturbation vector controls allowed dimensions for an individual. If an element of the perturbation vector is set to zero, then the individual is not allowed to change its position in the corresponding dimension.

An individual will travel a certain distance (called the Path Length) towards the leader in n steps of defined length. If the Path Length is chosen to be greater than one, then the individual will overshot the leader. This path is perturbed randomly.

There are specified following parameters of SOMA algorithm:

Cost function: determines how to evaluate individuals.
Specimen: describes a form of individuals
Population size: the number of individuals in the population which is contained in one migration.
Migrations: the maximum number of migrations to complete. (This parameter represents the maximum number of iteration).
Step: the step size of individual during migration
Path Length: duration of path which individuals use for migration
PRT: perturbation of migration
Minimal diversity: diversity of evolutionary process

More detailed description of SOMA can be found in [25],[26].

There are many of SOMA variations which are differentiated by way of migration. In our case, SOMA-All-To-All variation has been chosen, in which all individuals move towards the other individuals. This strategy often needs less cost function evaluations to reach the global optimum than the other strategies.

4 Simulation and Result

4.1 Synchronization of 5D Lorenz chaotic system'

In this section, we apply the Pecora and Carroll technique to achieve the synchronization between two identical 5D chaotic systems. The mathematical description of 5D system is as follows [10]:

$$U = \begin{cases} \dot{x} = a(y-x) \\ \dot{y} = rx - y - zx \\ \dot{z} = xy - bz + 2uw \\ \dot{u} = -cau + 2(a/c)w \\ \dot{w} = -2uz + 2ru - cw \end{cases} \tag{5}$$

where x, y, z, u and w are the state variables, and a, b, c and r are the positive real constants. The 5D system (5) exhibits a chaotic attractor for a = 10, b=8/3, c = 2 and r=24.75 as shown in Fig. 1.

We use a subscript **d** to denote the signals in the drive, and a subscript **r** for the signals in the response. Using x of the decomposed subsystems as the driving signal, in this case, x was injected into the response system. Since $x_d = x_r = x$, we only consider the following drive and response subsystems:

$$U_d = \begin{cases} \dot{y} = rx - y_d - z_d x \\ \dot{z} = x\, y_d - bz_d + 2u_d w_d \\ \dot{u} = -cau_d + 2(a/c)w_d \\ \dot{w} = -2u_d z_d + 2ru_d - c_d w_d \end{cases} \tag{6}$$

And the response system U_r is described by the following equations:

$$U_r = \begin{cases} \dot{y} = rx - y_r - z_r x \\ \dot{z} = x\, y_r - bz_r + 2u_r w_r \\ \dot{u} = -cau_r + 2(a/c)w_r \\ \dot{w} = -2u_r z_r + 2ru_r - cw_r \end{cases} \tag{7}$$

where a, b, c and r are unknown parameters in response system.

Consider the difference of these two systems $\mathbf{e} = \mathbf{U_d} - \mathbf{U_r}$, the synchronization of the pair of identical systems (6) and (7) occurs if the dynamical system describes the evolution of the difference $|\boldsymbol{U_d(t)} - \boldsymbol{U_r(t)}| \rightarrow 0$ as $t \rightarrow \infty$. Subtracting system (6) from system (7) yields the error dynamical system between two system $\mathbf{e(t)} = \boldsymbol{U_d(t)} - \boldsymbol{U_r(t)}$ were used to create a cost function CF representing the root mean square error (RMSE) of synchronization between $\mathbf{U_d}$ and $\mathbf{U_r}$:

$$\text{CF}=\sqrt{\frac{1}{m}\sum_{t=1}^{m}|U_d(t)-U_r(t)|^2} \tag{8}$$

The parameter estimation can be formulated as a multidimensional nonlinear problem to minimize the cost function CF. SOMA are used to find a suitable parameter a, b, c and r such that the cost function CF can be asymptotical approach to minimum point. The minimum value of cost function guarantees of the best solution with suitable parameters. Systems are asymptotically (and globally) synchronized.

4.2 Parameter setup

In our simulations, the initial states of the drive system (6) and the response system (7) are taken as $x_d(0) = x = 1$, $y_d(0) = 2$, $z_d(0) = 1$, $u_d(0) = 1$, $w_d(0) = 1$ and $x_r(0) = x = 1$, $y_r(0) =-2$, $z_r(0) =-1$, $u_r(0) = -1$, $w_r(0) = -1$, respectively. Hence the error system has the initial values $e_x(0) = 0$, $e_y(0) = 4$, $e_z(0) = 2$, $e_u(0) = 2$ and $e_w(0) = 2$.

Table 1 SOMA parameter setting

Parameter	Value
Population size	20
Migrations	20
Step	0.11
Path length	3
Perturbation	0.1
Minimal diversity	-1

SOMA-All-To-All was used to solve the systems, which the control parameters setting are given in Table1 1. Simulations were implemented using Mathematica programming language and executed on Pentium D 2.0G, 2GB personal computer.

4.3 Experimental results

4.3.1. Case study 1: simulation on one-dimensional parameter estimation

In this case, one-dimensional parameter estimation is considered. That mean three parameters are known in advance with the original value; one parameter "**a**" is unknown and need to be estimated. The initial guesses are in the range [5, 15] for a, the control parameters were set as Table 1. SOMA-All-To-All has found the best results were collected as Table 2, both the worst and the best values of the cost function approaches minimum value quickly after 3 migrations as shown in Fig.2.a. SOMA had found the optimum value of "**a**" as shown in Fig.2.b.

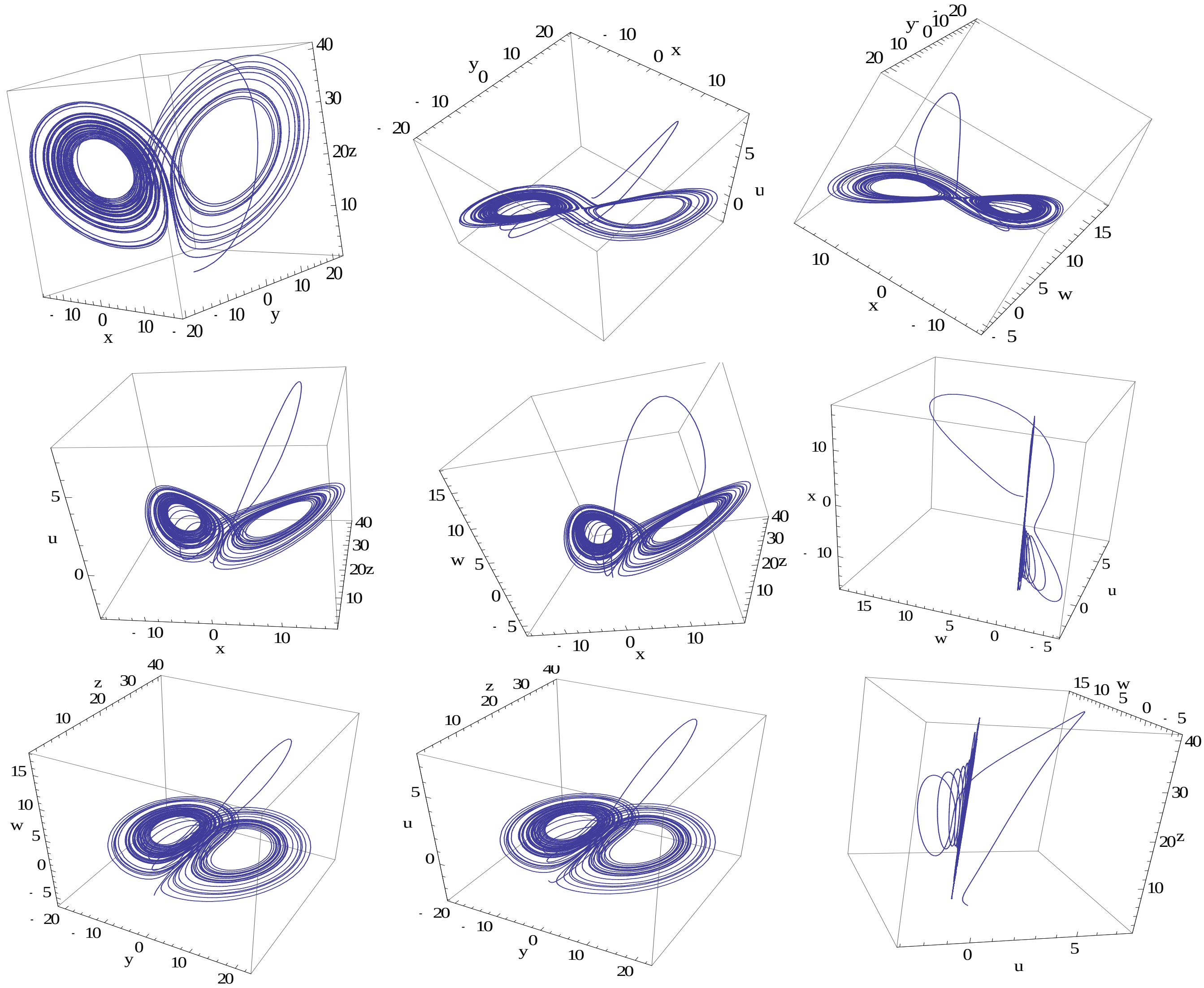


Fig. 1 Views of the chaotic attractor of 5D chaotic system

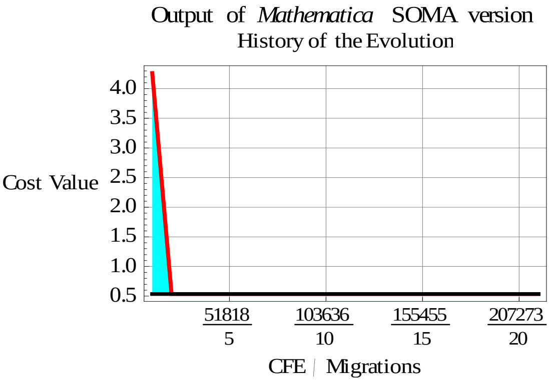


Fig.2.a. CF_a evolution by SOMA

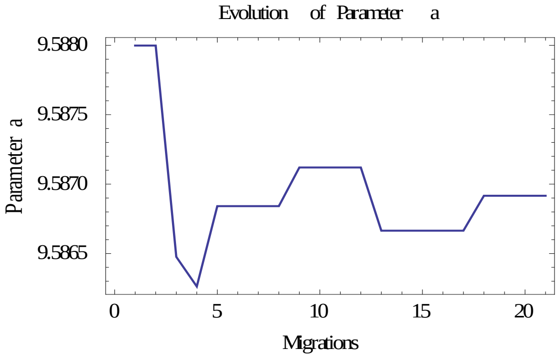


Fig.2.b. Evolution history of a

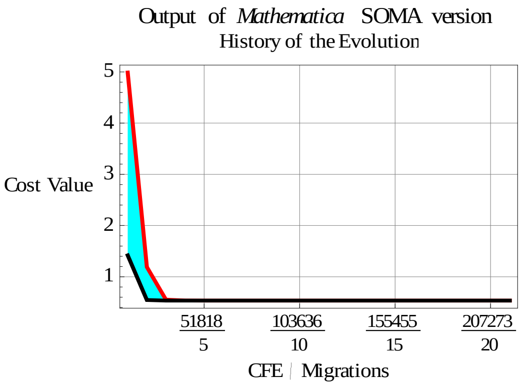


Fig.3.a. CF_b evolution by SOMA

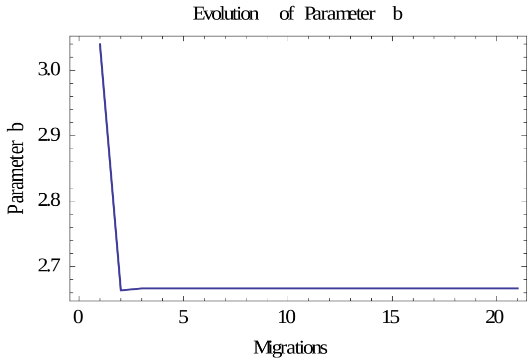


Fig.3.b. Evolution history of b

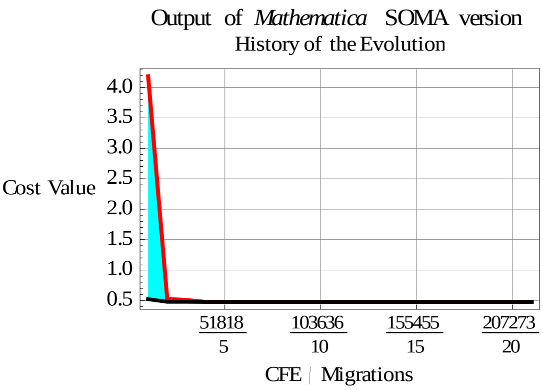


Fig.4.a. CF_c evolution by SOMA

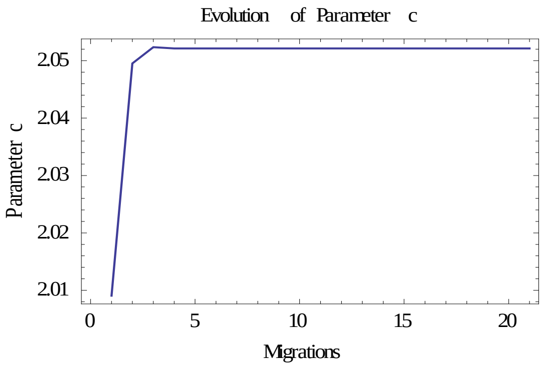


Fig.4.b. Evolution history of c

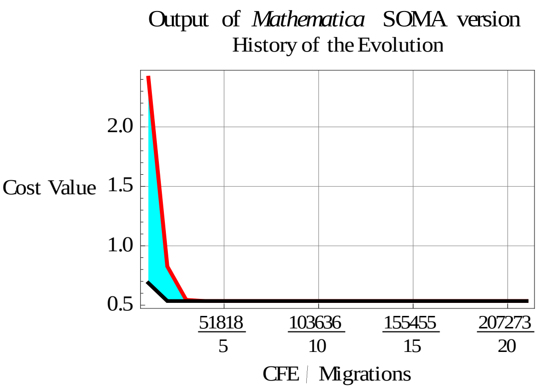


Fig.5.a. CF_r evolution by SOMA

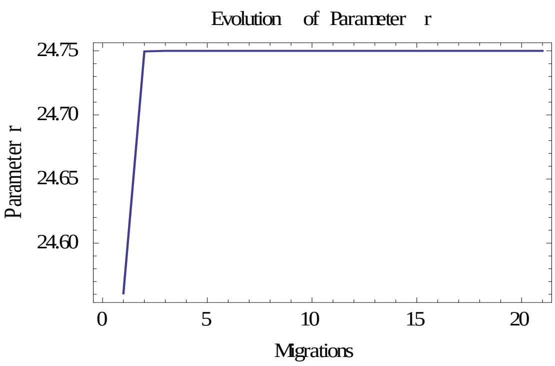


Fig.5.b. Evolution history of r

Similar for the others, the initial guesses are in the range for $b \in [0,5]$, $c \in [0,5]$ and $r \in [20,30]$; the estimated parameter b,c,r also were found by SOMA as shown in Fig.3,4,5.b. The values of CF also quickly approached to optimum values as seen in Fig.3,4,5.a. The estimated parameters and minimum CF values were presented in Table 2. It can be seen that the best results (estimated values) obtained by SOMA-All-To-All are almost the same and very close to the true values.

Table 2. 1D Estimated parameters by SOMA

Estimated parameters		Cost function
a	9.58692	0.533740
b	2.66667	0.534797
c	2.05214	0.478853
r	24.7500	0.534797

4.3.2. Case study 2: simulation on four-dimensional parameter estimation

Four-dimensional parameter estimation is considered in this case. That mean all of parameters a, b, c and r of response system were unknown and need to be estimated, the control parameters a,b,c and r were known in advance with original value in driver system.

The initial guesses are in the range for $a \in [5, 15]$, $b \in [0,5]$, $c \in [0,5]$ and $r \in [20,30]$ and the control parameters of SOMA were set as Table 1. Because of the sensitive of chaotic system, the cost function CF is so complex and has a lot of local optimum. But after 5 migrations, SOMA-All-To-All has found the best results of CF=0.476868, the best values of the cost function approached minimum value quickly. Both the worst and the best values of cost function approached minimum gradually after 8 migrations as shown in Fig.7. SOMA had found the optimum value of a,b,c and r as shown in history evolution (Fig.6), the estimated parameters have the similar value with original parameters. It can be seen that the best results (estimated values) obtained by SOMA-All-To-All are almost the same and very close to the true values as shown in Table 3.

Table 3. 4D Estimated parameters by SOMA

Estimated parameters				Cost function
a	b	c	r	
9.7775	2.66667	2.05443	24.75	0. 476868

Table 4. 2D Estimated parameters by SOMA

Estimated parameters			Cost function
a,b	9.58676	2.66667	0.533740
a,c	9.77759	2.05443	0.476897
a,r	9.58691	24.7500	0.533740
b,c	2.66667	2.05214	0.478853
b,r	2.66667	24.7500	0.534797
c,r	2.05215	24.7500	0.478853

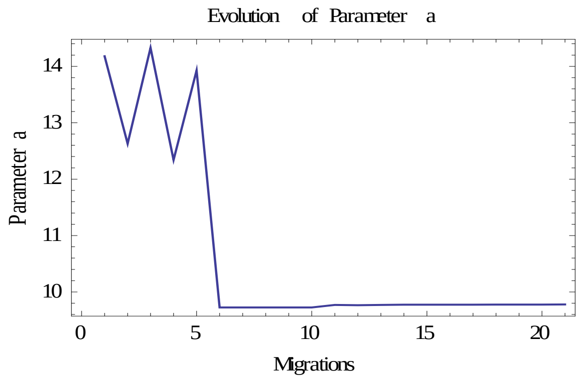


Fig.6.a. History evolution of parameter a

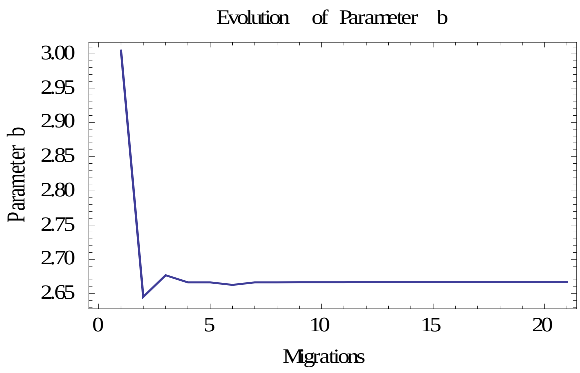


Fig.6.b. History evolution of parameter b

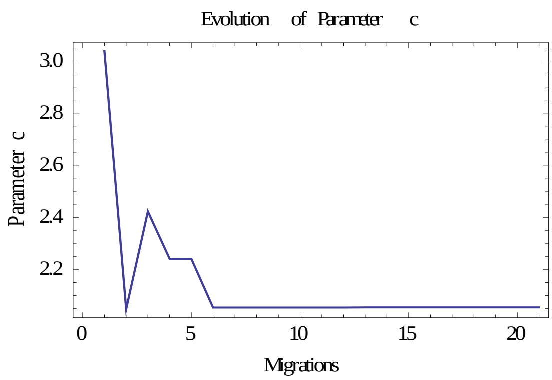


Fig.6.c. History evolution of parameter c

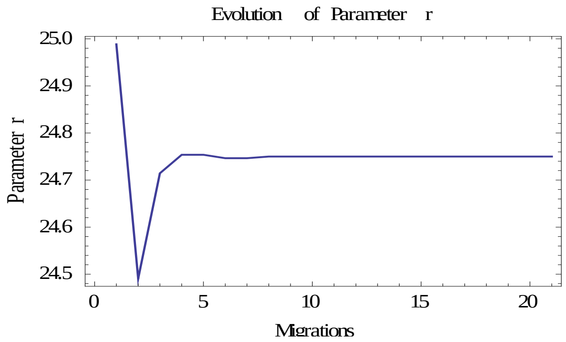


Fig.6.d. History evolution of parameter r

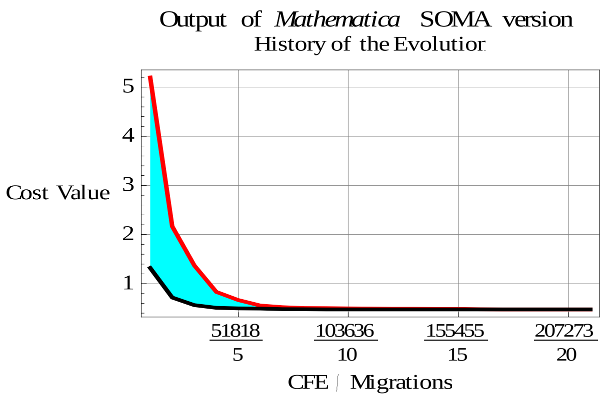


Fig.7. CF_{abcr} evolution by SOMA

Table 5. 3D Estimated parameters by SOMA

Estimated parameters				Cost function
a,b,c	9.77758	2.66667	2.05443	0.476897
a,b,r	9.58682	2.66667	24.7500	0.533740
a,c,r	9.77761	2.05443	24.7500	0.476897
b,c,r	2.66667	2.05214	24.7500	0.478853

In case 1 or 2 parameters among of a, b, c and r in response system were known in advance with the original value; the others (3 or 2) were also found with the optimum value by SOMA as shown in Table 4, 5. Both the worst and the best values of cost function quickly approach minimum after 8 migrations as shown in Fig.8, 9.

As shown in Table 2 – 5, the estimated parameters always have the similar values with original values. However, we can also easily recognize the effect of parameter ‘c’ on parameter 'a' and on system. The estimated parameter ‘a’ always tends to achieve a= 9.586xx with c=2 (such as in case study CF_a, CF_{ab},CF_{ar},CF_{abr}). While cost-functions CF always approach to area CF=0.47xxx with a=9.777xx when both 'a' and 'c' were estimated by SOMA (such as CF_{ac}, CF_{abc}, CF_{abcr}). The cost-functions CF=0.47xxx are smaller than CF=0.53xxx. So that, the final estimated values were chosen: a= 9.7775, b= 2.66667, c= 2.05443 and r= 24.75 to ensure that the synchronization error approaches to minimum. Thus, the actual parameters were fully identified. The values of cost function always approach to optimum values, the estimated parameters obtained by SOMA and original parameters have the similar values. So, it is demonstrated that SOMA is effective to estimate parameters for 5D-chaos synchronization system.

4.4 Synchronization of 5D chaotic system with estimated parameter

Based on the values estimated by SOMA, the response system was constructed. The effective of the estimated value on the synchronization errors of driver systems U_d and on response system U_r via PC method were demonstrated as shown in Fig.10-14.

As shown in Fig.10-14(a), the synchronization between driver system (dash line) and response system (red line) do not exist in the phase space of chaotic attractor. In the opposite, when PC was applied with the estimated parameters, Fig.10, 11, 14.(b) displays that the phase space of chaotic attractor between driver system and response system absolutely approached and synchronized although they were started under different initial values.

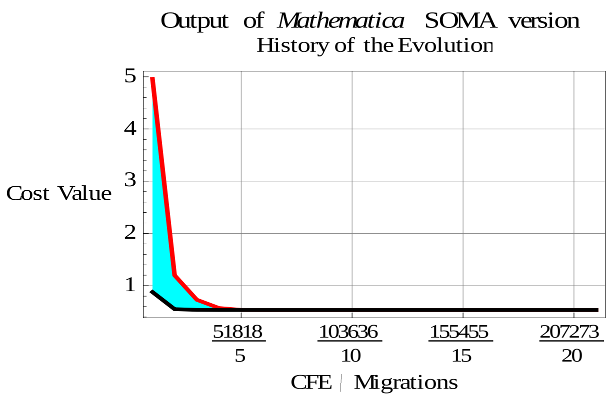


Fig.8. CF_{ab} evolution by SOMA

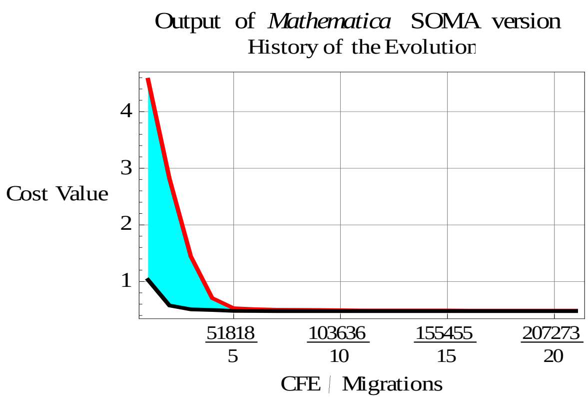
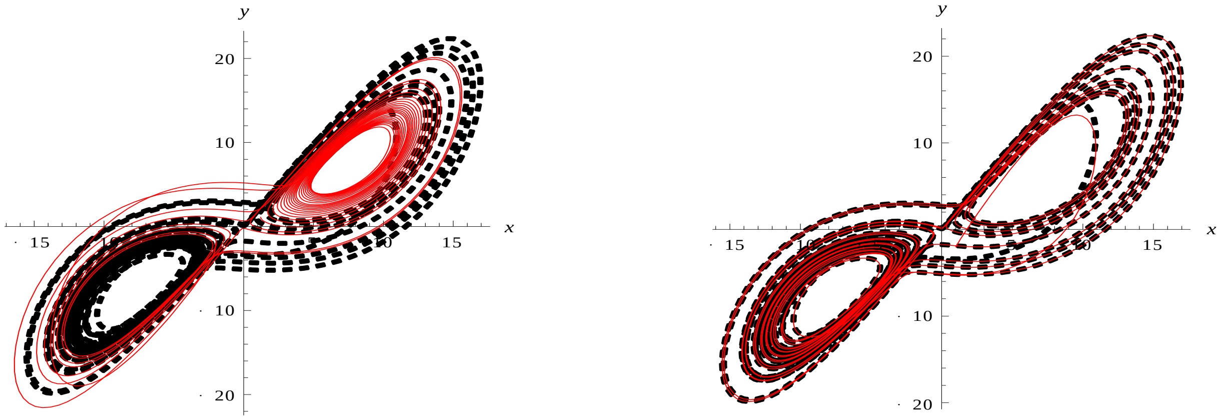
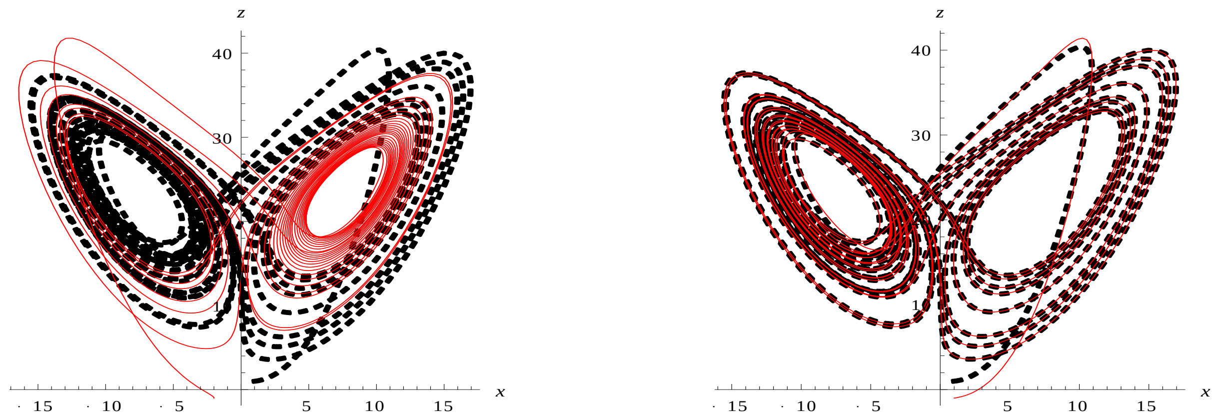


Fig.9. CF_{abc} evolution by SOMA



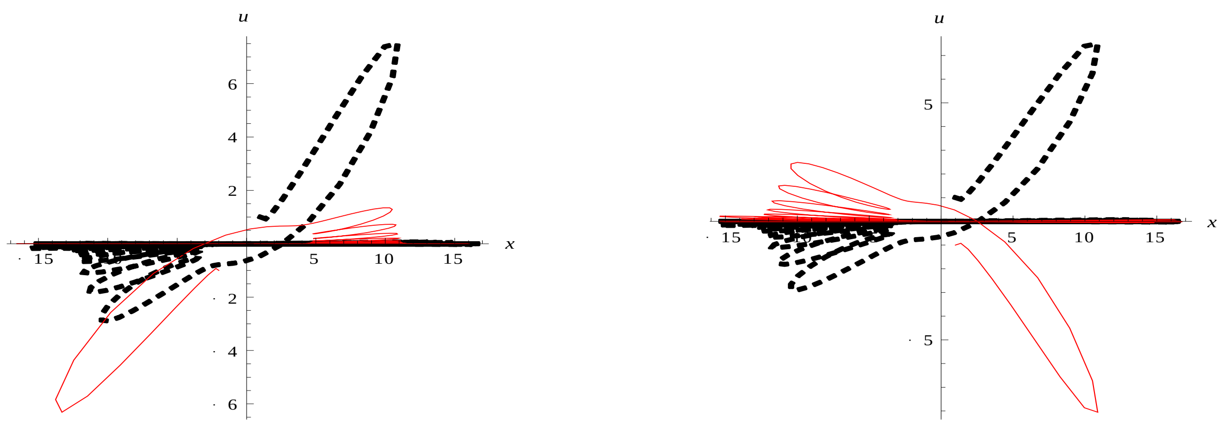
(a) (b)

Fig.10. Projection onto the x-y plane of the 5D Lorenz attractor. a) Non-synchronization. b) Synchronization with estimated parameters and PC method



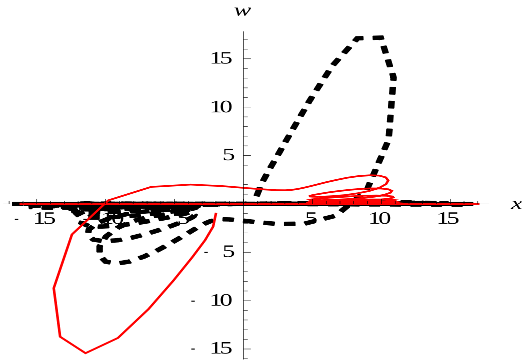
(a) (b)

Fig.11. Projection onto the x-z plane of the 5D Lorenz attractor. a) Non-synchronization. b) Synchronization with estimated parameters and PC method

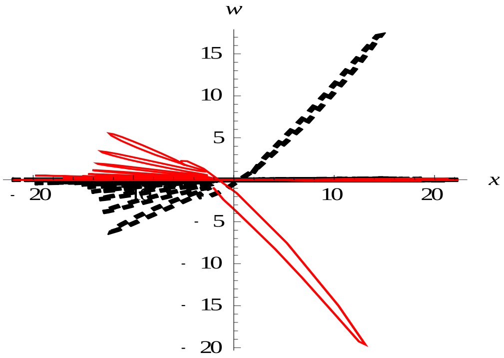


(a) (b)

Fig.12. Projection onto the x-u plane of the 5D Lorenz attractor. a) Non-synchronization. b) Synchronization with estimated parameters and PC method

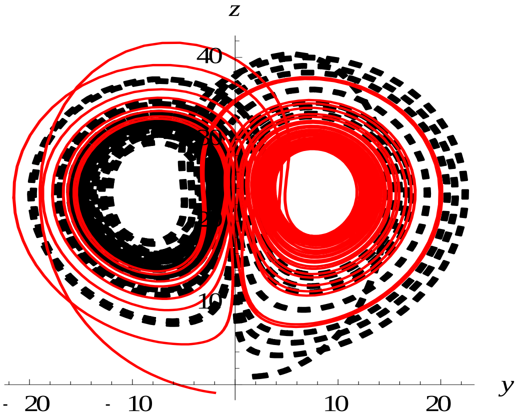


(a)

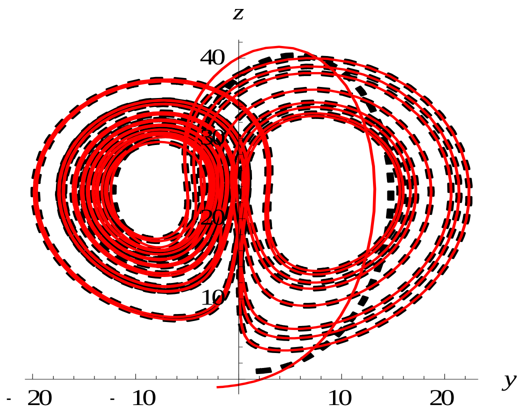


(b)

Fig.13. Projection onto the x-w plane of the 5D Lorenz attractor. a) Non-synchronization. b) Synchronization with estimated parameters and PC method



(a)



(b)

Fig.14. Projection onto the y-z plane of the 5D Lorenz attractor. a) Non-synchronization. b) Synchronization with estimated parameters and PC method

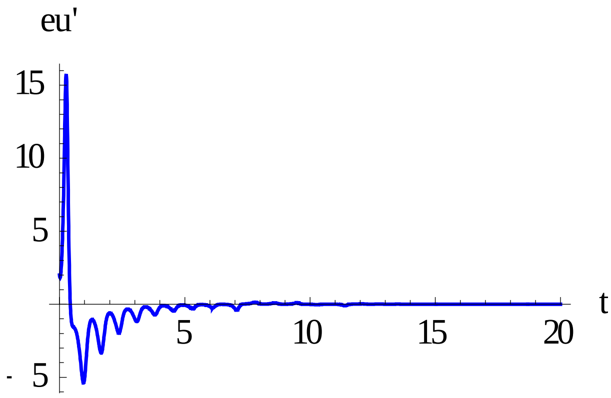


Fig.15.a. Synchronization error of variable ‘**u**’

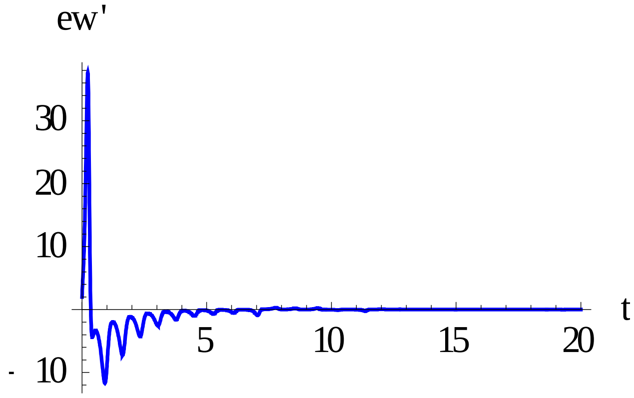


Fig.15.b. Synchronization error of variable ‘**w**’

It seems that there are not synchronization between driver system and response system of variable ‘**u**’ and ‘**w**’ in Fig.12.(b) and Fig.13.(b). But Fig. 15 showed that the synchronization error of e_u & e_w approach to 0 after t>10. That means the synchronization was achieved when both variables ‘**u**’ and ‘**w**’ approached 0 with t>10. This is a characteristic of these 5D chaotic systems as shown in Fig.1. Therefore, it is demonstrated that the estimated values and PC method are effective to synchronize for two 5D-chaotic systems.

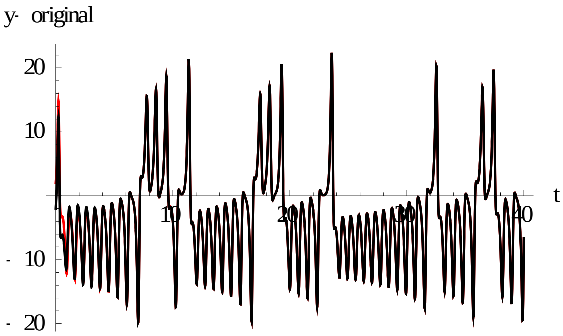


Fig.16.a. Synchronization with original values

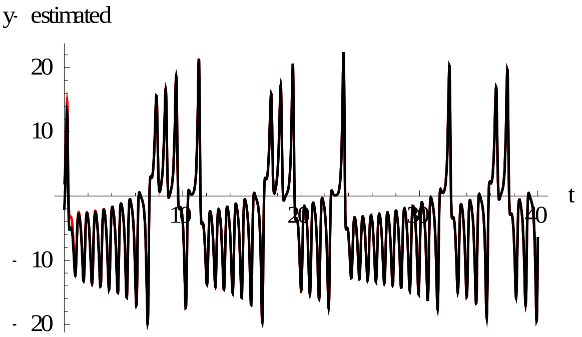


Fig.16.b. Synchronization with estimated

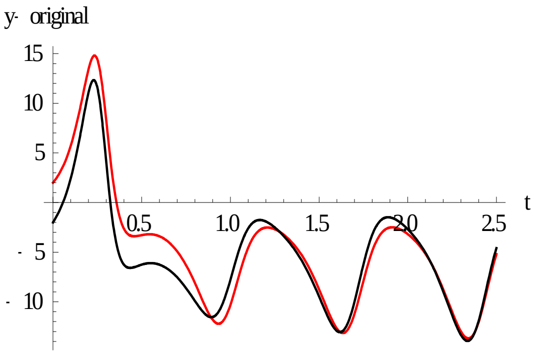


Fig.16.c… and its detail

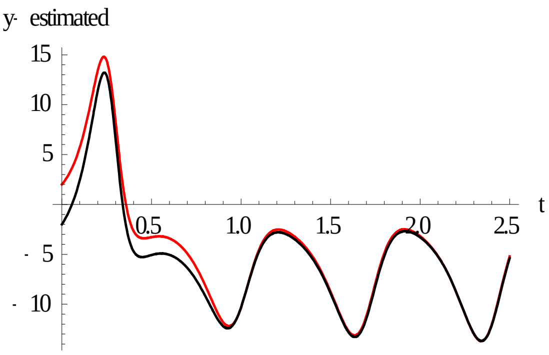


Fig.16.d… and its detail

5 Conclusions

The main aim of this research is to show that evolutionary algorithms were used as a method of artificial intelligence to estimate parameters of chaotic synchronization systems. In this paper, the PC method was applied to synchronize two identical 5D-chaotic systems. Parameter estimation for chaotic synchronization system was formulated as a multidimensional optimization problem. Because of the irregular dynamic behavior of chaotic systems, there is a lot of local optimum in the landscape of cost function. Self-Organizing Migration Algorithm was used to estimate the optimum values for unknown parameters, and it easily escaped the local optimum trap and achieved the global optimum parameters. Based on the estimated parameter from SOMA, two chaotic systems were synchronized absolutely.

It is difficult to recognize what differs Fig.16.a from Fig.16.b, but in its detail as shown in Fig.16.c and Fig.16.d, the quality of synchronization with estimated parameters is clearly higher than that of original parameters from t > 0.9. That mean the quality of communication system is increased with the estimated parameters.

In order to improve security in chaos communication system, one would require either a much higher sensitivity of synchronization method (or more optimal of system parameters to synchronize) or a system with higher dimensionality in order to increase the number of degrees of freedom an enemy would have to scan in order to synchronize, which may happen in lower system. As the future subject, it can be extended to other synchronization method to find the more suitable, which method is much stronger of synchronization. It can also be extended to the other systems which will consider the synchronization of two different systems or the effects of noise, fading, offset, etc. in communication system.

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