Controlling Complexity

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Abstract. Complex systems and dynamics are present in many parts of daily life and branches of science. This participation is continuation of our previous research, that introduced a novelty method of visualization and possible control of complex networks, that are used to visualize dynamics of evolutionary algorithms. Selected evolutionary algorithms are used as an example in order to show how its behavior can be understood as complex network and controlled via conversion into CML system - a model based on mutually joined nonlinear *n* equations. The main aim of this investigation was to show that dynamics of evolutionary algorithms can be converted to CML system and then controlled. Selected results of evolutionary controlled CML system are discussed here.

Keywords: complex networks, deterministic chaos, control, evolutionary dynamics
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INTRODUCTION

In this article, we continue in intersection of two interdisciplinary research areas: complex networks and evolutionary computation. As has been demonstrated in [4], [3], dynamics of evolutionary algorithms can be converted into complex network structure and this structure can be converted into CML (Coupled Map Lattices) system [1]. As has been proven and numerically demonstrated, see [2], such system is controllable by classical control methods as well as by evolutionary algorithms. This chain of conversions is very important, because is allows us to control not only dynamics of complex network, but also dynamics of observed evolutionary algorithm. Principle of above mentioned conversion between complex network and CML is demonstrated in Figure 1 and 2.

The main idea of our research is to show in this participation that the dynamics of evolutionary algorithms, in general, shows properties of complex networks and can be visualized like a complex networks and controlled like CML system. This contribution introduces continuation of an investigation on CML system control by means of selected evolutionary techniques. CML behavior is specially defined and simulated with spatiotemporal chaos model based on mutually nonlinear joined *n* equations, see [1]. Four evolutionary algorithms were used for chaos control here: differential evolution, self-organizing migrating algorithm, genetic algorithm and simulated annealing. Simulations numerically demonstrated that evolutionary algorithms are capable of control of CML systems, very often exhibiting deterministic chaos. All data were processed and used in order to get summarizing results and graphs.

Experiment Design

Used hardware

All experiments have been done on a special server consisting of 16 Apple XServer (2 x 2 GHz Intel Xeon, 1 GB RAM,), each with 4 CPU, so in total 64 CPUs were available for calculations. It is important to note here, that such technology was used to save time due to a large number of calculations, however it must be stated that evolutionary identification described here, is also solvable on a single PC (with longer execution time). For all calculations and data processing, Mathematica version 8 was used.

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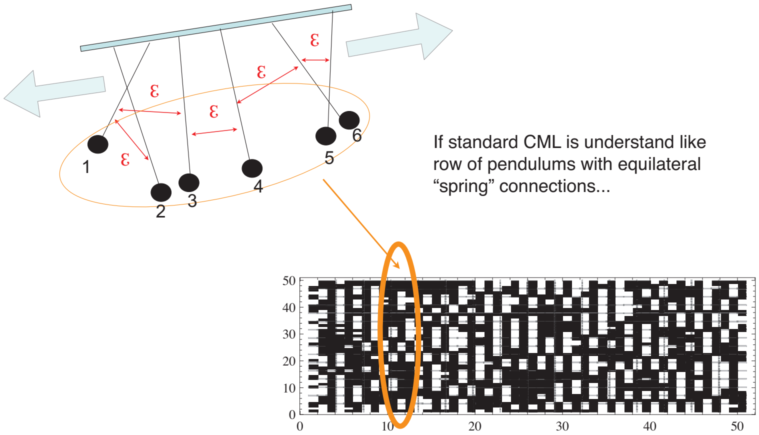
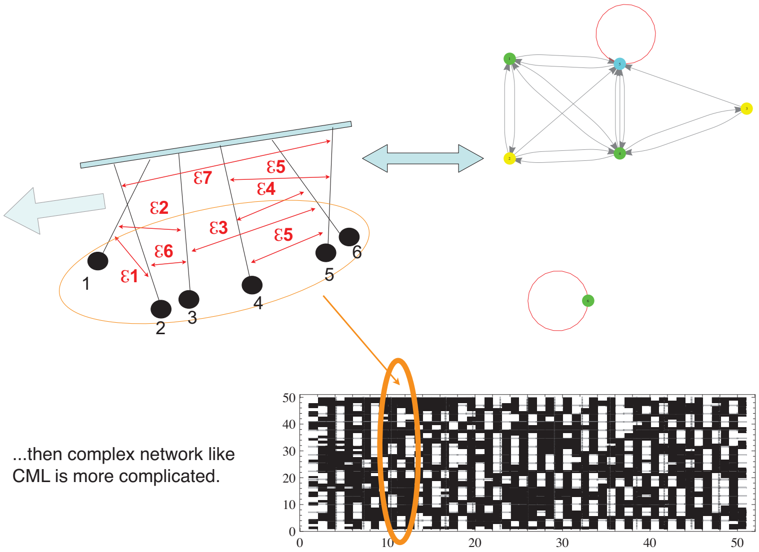


If standard CML is understand like
row of pendulums with equilateral
“spring” connections...

FIGURE 1. Classical CML system, each row can be understand like a pendulum that is connected with nearby pendulums via $\varepsilon \in [0,1]$, see [1].



...then complex network like
CML is more complicated.

FIGURE 2. CML system reflecting complex network structure, each row can be understand like a pendulum that is connected with arbitrarry pendulums (i.e. connections between vertices) via $\varepsilon \in [0,1]$, see [3].

Controlling CML

The class of CML problems chosen for this comparative study was based mostly on case studies reported in [1] and partially on [5], [6]. In general, controlling of the CML means setting of such pinning sites (control CML sites) and their pinning values (control inputs) so that system stabilizes itself on expected spatiotemporal pattern (like for example on T1S2 âĂŞ time period 1, space period 2). Computer simulations were designed so that they would simulate real-time CML process (i.e. running evolutionary algorithm, EAs), based on following philosophy: real-time means that there is no way to return back CML state and initial conditions, which means that CML has to run, for new calculations of pinning inputs, further in time. To combine use of EAs, a little change was done in contrary with âĂIJnon real-time controlâĂİ published in for example in [7], [8], [9], [10]. Simply, EA process, i.e. individuals and population development has followed CML behavior in time in a way that a certain number of CML iterations were reserved for evaluation of each individual in the population.

Fitness Function and Used Algorithms

The fitness (cost function) has been calculated according to the distance between the desired CML state and the actual CML output of Equation (1). The minimal value of the cost function (1), guarantee of the best solution, is 0. The aim of all simulations based on (1) was to find the best solution, i.e. a solution that returns the lowest cost value possible. Used algorithms were differential evolution and SOMA.

$$
\begin{array}{l}
f_{\cos t} = \sum\limits_{i=1}^{20} \sum\limits_{j=m}^{m+n} \left| TS_{i,j} - CML_{i,j} \right|^{2} \\
\mathrm{TS}_{\mathrm{i,j}} - \text{target state of CML} \\
\mathrm{CML}_{\mathrm{i,j}} - \text{actual state of controlled CML} \\
m - \text{actual iteration of the CML} \\
n - \text{iterations}
\end{array}
\qquad (1)
$$

Conclusion

The main motivation of this research is whether it is possible to control and simulate underlying dynamics of an evolutionary process as a complex network and CML system. Based on preliminary results it can be stated that simulations has numerically demonstrate that dynamic of evolutionary algorithms can be visualized like a complex network and controlled via its conversion into CML system. For controlling of CML system has been selected EAs because of its ability to avoid local extremes, which are densely present in the fitness surface of complex systems like CML are. Typical examples of very complex cost functions generated by systems like CML (i.e. deterministic chaos systems) is are depicted on Figure 3. It is clearly visible that EAs are one of a few techniques that are able to locate global extreme on such a surface. Its coordinates then guarantee optimal control. Selected examples of controlled and stabilized CML systems by means of EAs are in Figure 4 and 5. From figures is visible that stabilization has been reached successfully and thus controlling of CML systems as well as based on complex networks (Figure 2)) is possible. Concerning to proposed method, that is based on evolutionary computation, it is true (see [2]), that it is able to control wide spectra of dynamic systems including deterministic chaos and spatiotemporal chaos. An advantage of evolutionary techniques is that they are able to solve problems with large unknown parameters, that has to be estimated.

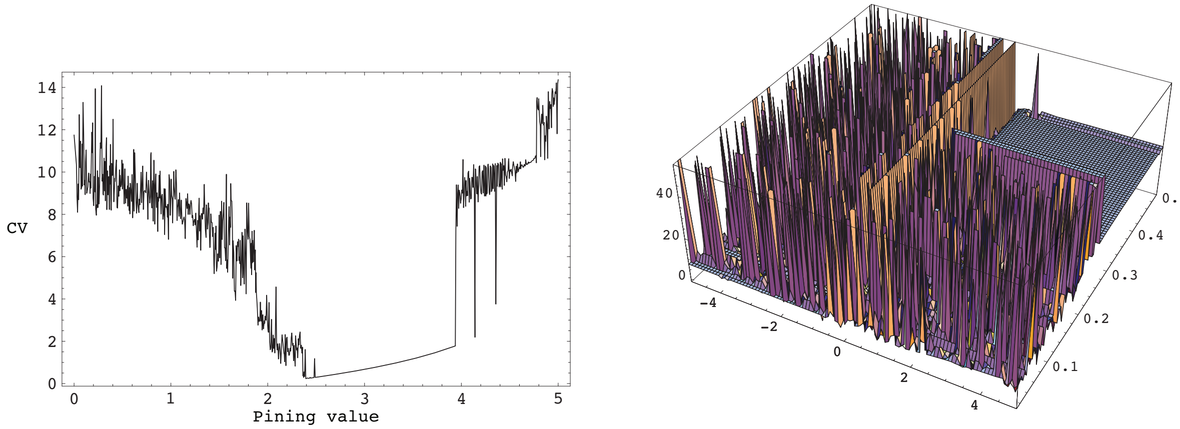


FIGURE 3. Cost function surface for chaotic system with one (left) and two (right) controllable parameter.

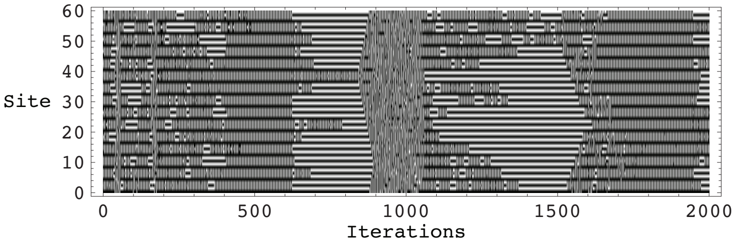


FIGURE 4. CML control, deterministic windows are visible in chaotic behavior of used CML.

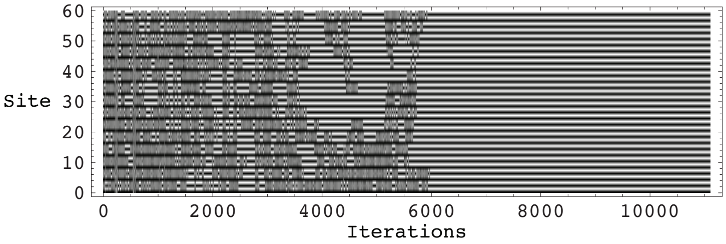


FIGURE 5. CML control, deterministic windows are visible in chaotic behavior of used CML. Stabilization is finally achieved.

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