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Data-based fuzzy modelling of dynamic systems by means of evolution strategies

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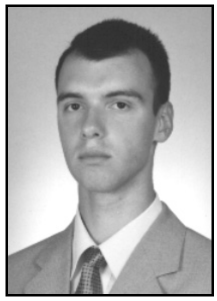

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Abstract

The paper presents a hybrid approach (combining fuzzy rule-based systems and evolution strategies) to modelling of complex dynamic systems and processes using data that describe their behaviour. The application of the proposed approach to modelling and prediction of the Mackey-Glass chaotic time series is also presented in the paper. This time series – of complex dynamics – describes various physiological and technical control systems.

Keywords: computational intelligence, fuzzy systems, evolution strategies, evolution-strategy fuzzy systems, measurement data.

Rozmyte modelowanie systemów dynamicznych na bazie danych z wykorzystaniem strategii ewolucyjnych

Streszczenie

Artykuł prezentuje hybrydowe podejście – łączące rozmyte systemy regułowe z tzw. strategiami ewolucyjnymi – do modelowania złożonych, dynamicznych systemów i procesów z wykorzystaniem danych opisujących ich zachowanie. Strategie ewolucyjne stanowią jedną z czterech głównych klas algorytmów ewolucyjnych – obok najbardziej popularnych algorytmów genetycznych, programowania ewolucyjnego oraz programowania genetycznego. Szereg cech strategii ewolucyjnych – w tym samoadaptacja parametrów sterujących strategią ewolucji, co umożliwia dokładne lokalne dostrajanie się algorytmu – powoduje, że są one interesującym narzędziem szczególnie w zagadnieniach optymalizacji z ciągłymi parametrami. Stąd też mogą być efektywnie wykorzystywane w budowie rozmytych regułowych modeli systemów oraz algorytmów sterowania na bazie danych. W artykule przedstawiono zastosowanie proponowanego podejścia do modelowania i predykcji tzw. chaotycznego szeregu czasowego Mackey-Glass'a. Szereg ten – o złożonej dynamice – opisuje różnorodne fizjologiczne i techniczne systemy sterowania. Przedstawiono uzyskaną bazę reguł modelu rozmytego, kształty funkcji przynależności zbiorów rozmytych w nim występujących oraz porównanie odpowiedzi modelu z danymi rzeczywistymi.

Słowa kluczowe: inteligencja obliczeniowa, systemy rozmyte, strategie ewolucyjne, systemy rozmyte z wykorzystaniem strategii ewolucyjnych, dane pomiarowe.

1. Introduction

In papers [5, 6] included in this volume, two different approaches to fuzzy rule-based modelling of dynamic systems and controller design are presented. Both approaches use data (also measurement data) that describe the behaviour of the systems and control processes as a basis for designing appropriate fuzzy rule-based models and controllers. The proposed techniques aim at obtaining fuzzy models (controllers) that are characterized by as good compromise as possible between the high accuracy and high transparency, interpretability and ability to explain the generated actions. In order to achieve this goal, the approach of [6] – belonging to the field of the so-called computational intelligence (CI), cf. [4] – employs the genetic fuzzy solution that formulates the fuzzy rule-based model (controller) design as a structure- and parameter-optimization problem. In turn, the approach of [5] – in order to achieve the afore-mentioned goal – proposes a novel combination of fuzzy rule-based systems with the multi-agent particle swarm optimization (PSO) technique for optimizing sets of fuzzy control rules synthesized from the control data.

This paper presents another approach to achieve the afore-mentioned goal, that is, a combination of fuzzy rule-based systems and the so-called evolution strategies (henceforward: ESs), cf. [2], [11]. ESs belong to a broader class of evolutionary algorithms that comprises also genetic algorithms, evolutionary programming and genetic programming, cf. [9]. ESs share common features of evolutionary algorithms, that is, a population of genetic structures, a selection mechanism that exploits promising regions of the search space as well as the recombination and mutation operators to generate new solutions. However, there are also significant differences between ESs and other evolutionary algorithms – in particular, genetic algorithms (GAs) that have been employed in [6]. Whereas in GAs the mutation is a secondary operator useful in preventing premature convergence of the population, in ESs the mutation plays a central role. The opposite holds for the recombination operator (the first ES did not employ that operator at all). The selection operator in ESs is entirely deterministic. A distinguishing feature of ESs is a self-adaptation of additional so-called strategy parameters. It enables ESs to adapt the process of evolutionary optimization to the structure of the fitness function surface. Due to these features, ESs – despite the fact that they are much less popular than GAs – seem to be an interesting tool, particularly in continuous optimization problems. For these reasons they attracted our attention as a promising technique in designing fuzzy rule-based models and controllers from data.

In this paper, first – based on [6] – the problem of the fuzzy rule-based model design of dynamic systems using data is briefly formulated. Then, an ES-based learning of fuzzy rules from data is outlined. Finally, the application of the proposed approach to modelling and prediction of the so-called Mackey-Glass chaotic time series (cf. [10]) is presented. This time series – of complex dynamics – describes various physiological and technical control systems, cf. [1, 3].

2. Fuzzy rule-based modelling of dynamic systems from data [6]

The concept of the fuzzy rule-based modelling of dynamic systems using data is presented in [6]. Here, for the convenience of the reader, the basic elements of that concept will be presented. Consider a dynamic system with r inputs $u_1, u_2, ..., u_r$ ($u_c \in U_c$, $c = 1,2,...,r$) and s outputs $z_1, z_2, ..., z_s$ ($z_d \in Z_d$, $d = 1,2,...,s$)

and assume that its behaviour is described by T input-output data samples:

$$D = \{\boldsymbol{u}'_t, \boldsymbol{z}'_t\}_{t=1}^{T} , \quad (1)$$

where $\boldsymbol{u}'_t = (u'_{1t}, u'_{2t}, ..., u'_{rt}) \in \boldsymbol{U} = U_1 \times U_2 \times ... \times U_r$ and $\boldsymbol{z}'_t = (z'_{1t}, z'_{2t}, ..., z'_{st}) \in \boldsymbol{Z} = Z_1 \times Z_2 \times ... \times Z_s$ ($\times$ stands for Cartesian product of ordinary sets). In particular, data (1) may have the form of time series

$$D = \{\boldsymbol{z}'_t\}_{t=1}^{T} . \quad (2)$$

Due to the system dynamics, the particular data records in (1) and (2) are interrelated, that is, data $\boldsymbol{z}'$ at present time instant t depends, in general, on data $\boldsymbol{z}'$ at previous time instances (for data (1) and (2)) and data $\boldsymbol{u}'$ at present and previous time instances (for data (1) only). The essential stage of fuzzy rule-based model design consists in determining the model structure in terms of its inputs and outputs (see [6] for details). Then, the initial descriptions (1) or (2) have to be reedited to the “static” form (according to the assumed model’s structure):

$$L = \{\boldsymbol{x}'_k, \boldsymbol{y}'_k\}_{k=1}^{K} , \quad (3)$$

where $\boldsymbol{x}'_k = (x'_{1k}, x'_{2k}, ..., x'_{nk}) \in \boldsymbol{X} = X_1 \times X_2 \times ... \times X_n$, $\boldsymbol{y}'_k = (y'_{1k}, y'_{2k}, ..., y'_{mk}) \in \boldsymbol{Y} = Y_1 \times Y_2 \times ... \times Y_m$, k is the number of model input-output static data pattern, $k = 1,2,...,K$. Data (3) are referred to as the learning data.

Fuzzy rules that will be synthesized from data (3) (for the case of single output system, that is, $m = 1$ and $y_1 = y$) by the proposed in Section 3 of this paper ES-based learning technique have the following form:

IF (x_1 is A_{1r}) AND … AND (x_n is A_{nr}) THEN (y is B_r), (4)

where $A_{ir} \in F(X_i)$, $i = 1,2,...,n$, and $B_r \in F(Y)$ are the S-, M-, or L-type fuzzy sets (see [7] for details) representing verbal terms Small, Medium and Large, respectively, in the r-th fuzzy rule, $r = 1,2,...,R$. $F(X_i)$ and $F(Y)$ denote families of all fuzzy sets defined in the universes X_i and Y, respectively.

3. Learning fuzzy rules from data via ESs

During the ES-based learning, a set of fuzzy rules (4) is created and the parameters of the input and output S-, M-, and L-type fuzzy sets of the rules (4) are tuned in order to minimize the assumed objective function. ESs process a population of individuals

$$\boldsymbol{a}_j = (\boldsymbol{w}_j, \boldsymbol{s}_j, F(\boldsymbol{w}_j)), \quad j = 1,2,...,J . \quad (5)$$

Individual $\boldsymbol{a}_j$ consists of object parameter vector $\boldsymbol{w}_j$ to be optimized, a set of strategy parameters $\boldsymbol{s}_j$ and the individual fitness $F(\boldsymbol{w}_j)$, which is the objective function in the considered optimization problems.

The standard ES versions are denoted as $(\mu/\rho, \lambda)$ or $(\mu/\rho + \lambda)$, where μ denotes the number of parents, $\rho \le \mu$ – the number of parents involved in the procreation of an offspring and λ – the number of offspring. The self-adaptive ES algorithm can be found in many references, cf. [9]. The common termination condition in that algorithm is reaching the assumed number of generations or finding a solution with acceptable value of the fitness function.

In the experiment reported later in this paper, the self-adaptive ES of $(\mu/2, \lambda)$ is applied [2]. An individual $\boldsymbol{a}_j$, $j = 1,2,...,J$ is defined as

$$\boldsymbol{a}_j = (\boldsymbol{w}_j, \sigma, F(\boldsymbol{w}_j)) . \quad (6)$$

The ES generates λ offspring by recombination of randomly selected pairs of individuals from parent population (discrete recombination is used where parents parameters are randomly transferred to the recombinant). Next, mutation operations are applied to the respective recombinants parameters according to following formulas:

$$\sigma'_j = \sigma_j \exp(\tau N_j(0,1)) , \quad (7)$$

$$\boldsymbol{w}'_j = \boldsymbol{w}_j + \sigma'_j \boldsymbol{N}_j(0,1) , \quad (8)$$

where $j = 1,2,\ldots,\lambda$, $N_j(0,1)$ are normally distributed random scalars and $\boldsymbol{N}_j(0,1)$ are normally distributed random vectors. The mutated strategy parameter σ'_j controls the strength of the object parameter mutation. The rate of the mutation self-adaptation depends on the value of the learning parameter τ (most often $\tau = 1/\sqrt{2 \dim \boldsymbol{w}_j}$, where $\dim \boldsymbol{w}_j$ is the dimension of vector $\boldsymbol{w}_j$).

4. Fuzzy rule-based modelling of the Mackey-Glass chaotic time series

The proposed ES fuzzy technique will now be used in the fuzzy rule-based modelling of the Mackey-Glass chaotic time series. This time series is generated by the Mackey-Glass differential equation [10]:

$$\frac{dx(t)}{dt} = \frac{0.2x(t-t_0)}{1 + x^{10}(t-t_0)} - 0.1x(t) . \quad (9)$$

The Mackey-Glass chaotic time series describes various physiological and technical control systems, cf. [1, 3]. The prediction of future values of this time series is a benchmark problem, which has been considered by a number of researchers, cf. [8]. The fourth-order Runge-Kutta method to find the numerical solution to (9) has been applied with the time step equal to 0.1, initial condition $x(0) = 1.2$ and $t_0 = 17$. 1000 data samples have been created. The first 500 samples are used as the learning data, and the remaining 500 samples – as the test data. The aim of the model is to predict the value $x(t+6)$ from the values $x(t-18)$, $x(t-12)$, $x(t-6)$ and $x(t)$. Therefore, the learning data (3) have the form:

$$\boldsymbol{x}'_k = (x'_{1k}, x'_{2k}, x'_{3k}, x'_{4k}) = (x(t-18), x(t-12), x(t-6), x(t)) , \quad (10)$$
$$y'_k = x(t+6) , \quad t = 18,19,...,517 , \quad k = t-17 , \quad K = 500 .$$

Each input and the output of the model is characterized by three verbal terms Small, Medium and Large. In the learning phase, the ES algorithm of $(\mu/2, \lambda)$ type with population sizes $\mu = 100$ and $\lambda = 500$ and the maximal number of generations equal to 500 has been used. In the learning process, the problem of the optimization of both the fuzzy rule base structure and its parameters has been addressed by the construction of the fitness function. It is a sum of two components: the first one is responsible for the accuracy of the model and the second one – for its transparency and interpretability “measured’ by the number of rules in the rule base. The first component is an aggregated mean squared error between the desired and actual activation degrees of the model output fuzzy sets – see [4] for details. The second component is a weighted number of fuzzy rules in the rule base.

Fig. 1 presents the plot of the fitness function for the best and average individuals versus the number of generations. Fig. 2 presents the final shapes of the membership functions of fuzzy sets describing model output y. Table 1 presents the full rule base generated by the proposed approach.

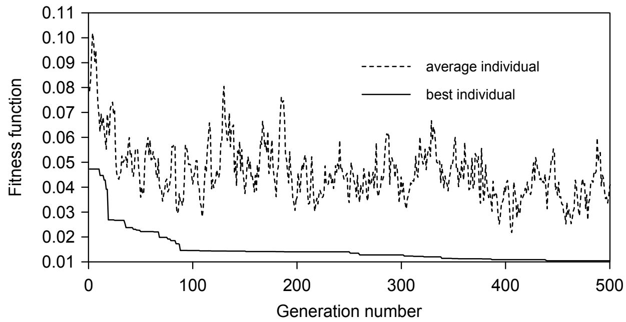

Fig. 1. Fitness function vs. iteration number plot
Rys. 1. Przebieg wartości funkcji dopasowania w trakcie procesu uczenia

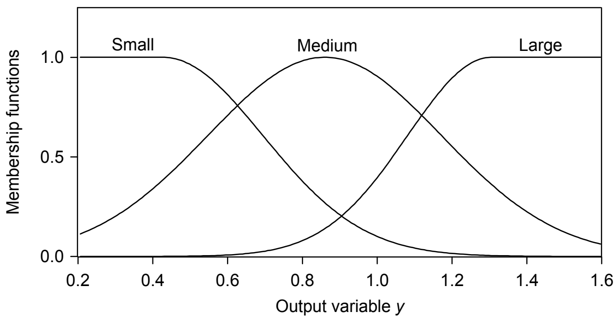

Fig. 2. Final shapes of membership functions of fuzzy sets describing the model output y
Rys. 2. Końcowe kształty funkcji przynależności zbiorów rozmytych opisujących zmienną wyjściową y modelu

Tab. 1. Final fuzzy rule base of the model
Tab. 1. Końcowa baza reguł rozmytych modelu

x_1	x_2	x_3	x_4	y
M	L	L	L	M
M	L	L	M	M
L	L	M	M	S
M	M	M	M	M
M	M	S	M	M
M	S	M	M	M
M	M	M	L	L
M	L	M	M	M

S=Small, M=Medium, L=Large

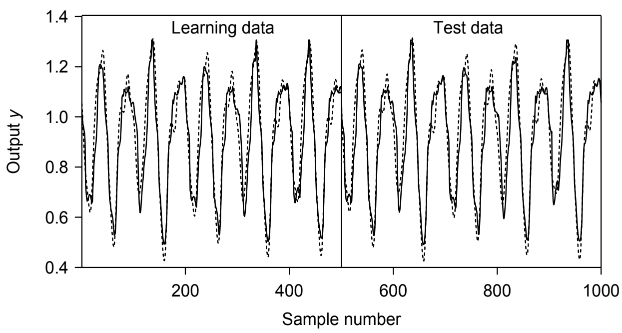

Fig. 3. Real (dashed line) and generated by the proposed model (solid line) Mackey-Glass time series
Rys. 3. Rzeczywisty (linia przerywana) i generowany przez proponowany model (linia ciągła) szereg czasowy Mackey-Glass'a

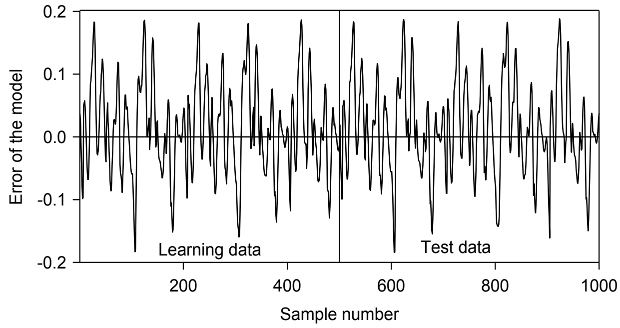

Fig. 4. Error of the model
Rys. 4. Błąd modelu

Fig. 3 shows the real values of the Mackey-Glass time series (dashed line) and the values generated by the proposed fuzzy rule-based model (solid line) for both learning and test data. Fig. 4 shows the error of the model (the differences between the real and generated values).

5. Conclusions

The hybrid approach – combining fuzzy rule-based systems and evolution strategies – to modelling of complex dynamic systems and processes using data that describe their behaviour has been briefly presented in this paper. Its performance has been successfully verified in a complex benchmark problem of modelling and prediction the Mackey-Glass chaotic time series.

This paper as well as papers [6] and [5] (in this volume) show that various computational intelligence techniques are very effective theoretical tools in data-driven, fuzzy rule-based intelligent modelling and control of complex systems and processes.

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