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Preface

This volume of Advances in Intelligent Systems and Computing contains papers presented at IITI 2017, the Second International Conference on Intelligent Information Technologies for Industry, which will be held on September 14–16 in Varna, Bulgaria. The conference was jointly co-organized by Technical University of Varna (Bulgaria), Technical University of Sofia (Bulgaria), VŠB Technical University of Ostrava (Czech Republic), and Rostov State Transport University (Russia).

The purpose of IITI 2017 was to bring together international researchers and industrial practitioners interested in the development and implementation of modern technologies for automation, informatization, computer science, artificial intelligence, transport, and power electrical engineering. The conference aimed at advancing both fundamental research and innovative applications, and sought to establish a new dissemination platform and an international network of researchers in these fields. Innovative information technologies were of particular interest to the conference. There were 235 paper submissions from 13 countries. Each submission was reviewed by at least three Chairs or PC members. The conference was selective and accepted 106 regular papers (45%) for presentation. Unfortunately, due to limitations of conference topics and edited volumes, the Program Committee was forced to reject some interesting papers which did not satisfy these topics or publisher requirements. We would like to thank all authors and reviewers for their work and valuable contributions. The friendly and welcoming attitude of conference supporters and contributors made this event a success!

July 2017

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Adaptive Approach for Anomaly Detection in Temporal Data Based on Immune Double-Plasticity Principle

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Abstract. The paper considers a new adaptive approach for anomaly detection and prediction in continuous time series. Presented approach is based on immune double-plasticity network. Antigens, which characterize temporal patterns or separated time samples, and antibodies, which characterize models for adaptive anomaly detection, are the basic classifiers in the proposed technique. The general idea of the approach is based on interaction between antigens and antibodies, when new time sample is observed. This interaction leads to the model adaptation with respect to input data based on prediction error minimization. In particular, flexible parametric fuzzy models are used as antibodies, which provide both parametric and structural adaptation simultaneously with input data processing. Appropriate trend of model parameters shows forthcoming anomaly and saltatory structure changing shows anomalous presence. Computational experiments for presented approach together with conventional regression models are illustrated.

Keywords: Flexible fuzzy models · Immune network with double-plasticity · Anomaly detection · Time series

1 Introduction

Temporal anomaly prediction tasks are very actual for many applications. In particular, anomaly prediction in temporal data is successfully utilized for abnormal technological behavior prediction in engineering systems [1], fault prediction in technical devices [2], intrusion detection in computer nets [3], accident prediction in ecological systems [4], etc.

The paper considers this task as anomaly detection in numerical time series, where anomalies are presented in form of the temporal patterns, which do not conform to expected behavior. Data defined by dynamic object behavior or by technological process is considered as continuous time series at the input of diagnosis system. Anomalies are referred to fault or deviation presence in dynamic behavior.

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2 General Approach for Anomaly Detection Based on Immune Double-Plasticity Principle

Immune approach for anomaly prediction is discussed in several papers [5,6], where immune models are constructed on the basis of negative selection algorithms. But these models just simplistically reflect one side of interaction process between immune system and its environment (as well as its reaction on external perturbations). Several unimplemented properties of immune systems may be useful for such engineering applications as image recognition, data prediction and data identification. In particular, key property of immune systems is internal double plasticity [7], which has not found workable application yet.

Double plasticity provides functioning of immune system even when external perturbations are permanent. It makes system be adaptive due to parameters and structure changing. Parametric plasticity is ability of a system to change functioning parameters to improve its efficiency during task execution. Structure plasticity is ability of a system to change structure by including new elements and excluding existing ones.

Nowadays, a little set of intelligent systems, where principles of double-plasticity are implemented, is known. For example, in [8], the memory training and supporting algorithm based on double-plasticity principles is developed to increase immune response after repeated contact with antigen is occurred. Double-plasticity is proposed for artificial neural network training [9] and for modelling of cellular automaton as well [10]. In these papers, antigens, or foreign cells representing input data, are objects under observation, and antibodies, or immunocompetent cells representing mathematical models, are recognizers and identifiers of these objects. When new data is observed at the input of a system (or new foreign cell is observed), antibodies try to identify them and stimulate the process of cloning by using smooth regulation of system parameters (or provide double-plasticity algorithm). When the set of active antibodies is big enough, the structure changing process is started, which leads to generation of substantially new antibodies. Structure changes leads to saltatory changes of a system, increasing its efficiency for data recognition and substantial data changes recognition. This property can be used as the basis in set of practical tasks.

Above described papers illustrate the main requirements, which should be satisfied by adaptive double-plasticity systems for diagnostics and prediction.

When new data is obtained at the input of a system, model parameters changes (which are performed as antibodies cloning) are made for its antibodies. Smooth parameters changes lead to saltatory structure changes, which are performed including new elements and/or excluding existing ones. Structure changes are defined by the internal parameter changes of a system during its adaptation and are not directly defined by external ones. Structure changes are based on simple heuristic algorithm, which is a sequence of fuzzy or probabilistic rules.

Obviously, that even the simplified process for foreign cells detection in immune system is much more complicated than the model based on negative selection algorithm. It justifies the attempt to use above mentioned properties

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of immune systems for adaptive diagnosis models with the aim of anomaly detection and prediction.

These principles show the important feature of double-plasticity systems, which reflects the nature of system, when external impacts and environment interactions take place. It means that immune reaction is just indirectly defined by interactions between antibodies and antigens. It is observed as system reorganization caused by these interactions during system adaptation.

3 Flexible Fuzzy System as Immune Antibody Model

The model imitating biological antibodies is the key element of artificial immune diagnosis system. It is intended for recognition of data represented as temporal patterns or time series:

$$S = x_1, x_2, \ldots, x_n, \tag{1}$$

where n is the pattern length, $x_i = x(t_i)$ is the time samples of pattern (or time series).

As the basis of immune system the following prediction model based on nonlinear autoregressive analysis is used:

$$x_i = F\left(x_{i-1}, \ldots, x_{i-k}\right). \tag{2}$$

This model predicts a time series sample based on previous ones. Let neuro-fuzzy system be used as prediction model to implement double-plasticity principles for autoregressive analysis. Flexible parameters are included into the neuro-fuzzy system to provide structure adaptation.

Implementation of flexible systems with structure adaptation is firstly proposed in [11], where it is described as a system with set of adjustable fuzzy operations. Adjustability is provided by soft variation between forms of functions, which can be used as fuzzy operations. Takagi-Sugeno neuro-fuzzy net (TS model) is used as the basis of flexible fuzzy prediction model [12]. Here, antecedents of rules are connected by t-norm, and consequents are normalized weighted sums of outputs. TS models can be presented in the following form for time series prediction:

$$\begin{aligned} R_r : \text{IF } \left(x_{i-1} = \alpha_{r_1} \text{ AND } x_{i-2} = \alpha_{r_2} \text{ AND } \ldots \text{ AND } x_{i-k} = \alpha_{r_k}\right) \\ \text{THEN } x_i^r = F_r(x_{i-1}, x_{i-2}, \ldots, x_{i-k}) \qquad \left(\forall r \in [1, N]\right), \end{aligned} \tag{3}$$

where N is the number of rules, $x_{i-1}, x_{i-2}, \ldots, x_{i-k}$ are the set of k previous time samples, α_{r_j} is the linguistic value for x_{i-j} at rth rule, $L_{a_j} : (x_{i-j} = \alpha_{r_j})$ is the elementary fuzzy sentence for rth rule antecedent x_{i-j}, $F_r(x_{i-1}, x_{i-2}, \ldots, x_{i-n})$ is the consequent of rth rule.

Output signal of TS model is calculated as follows:

$$x_i = \frac{\sum_{r=1}^{N} x_i^r \cdot T_{j=1}^{k}\left(J(L_{a_j})\right)}{\sum_{r=1}^{N} T_{j=1}^{k}\left(J(L_{a_j})\right)} \tag{4}$$

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where $T_{j=1}^{k}(*)$ is the t-norm under k values "$*$", $J(L_{a_j}) = \mu_{\alpha_{r_j}}$ is the truth value for elementary fuzzy sentence $L_{a_j} : (x_{i-j} = \alpha_{r_j})$, $\mu_{\alpha_{r_j}}$ is the membership function for linguistic value.

Flexible TS model, where soft choice of linguistic values is implemented for antecedent calculation, is constructed below. With this purpose, generalized parametric fuzzy sentence should be introduced as follows.

Let jth elementary sentence $L_{a_j} : (x_{i-j} = \alpha_{r_j})$, where variable x_{i-j} has unambiguous linguistic value α_{r_j}, correspond to fuzzy generalized parametric sentence (with parameter $w_j \in [0, 1]$), where variable x_{i-j} has a set of its possible linguistic values $A = \{a_l | l = 1, 2, ..., m\}$. Here, each a_l has its own "possibility rate" depending on w_j. Fuzzy generalized parametric sentence has the following form:

$$L_j : x_{i-j} = \alpha_1(w_j) \vee \alpha_2(w_j) \vee ... \vee \alpha_m(w_j). \tag{5}$$

Parameter w_j from L_j is established as follows.

Let $W = [-1, +1]$ denote a universe and $z_l (k = 1, 2, ..., m)$ denote a uniformly distributed support value, which corresponds to linguistic value $\alpha_l (l = 1, 2, ..., m)$. Let $\mu_E(w|w^*)$ denote membership function of arbitrary form and $w^* \in W$ denote its center, which is considered as a flexible parameter for sentence L_j. Truth value $J(L_j)$ is defined based on flexible parameter w^* as follows:

$$J(L_j|w^*) = \frac{\sum_{l=1}^{m} J(L_{\alpha_l}) \cdot \mu_E(z_l|w^*)}{\sum_{l=1}^{m} \mu_E(z_l|w^*)} \tag{6}$$

As value w^* is closer to z_l at universe W, as $\mu_E(z_l|w^*)$ is closer to one. Then, as value w^* is closer to z_l, as truth value of general parametric sentence (5) is closer to truth value of elementary fuzzy sentence $L_{a_l} : (x_{i-j} = \alpha_{r_l})$, where α_{r_l} is referred to z_l. Therefore, parameter w^* changes "presence rate" for elementary fuzzy sentences L_{a_l} at L_j. Truth value $J(L_j|w^*)$ can be varied depending on flexible parameter w^*, so it can be corresponded to any value $L_{a_l} : x_{i-j} = \alpha_l (l = 1, 2, ..., m)$ or represented by set of α_l, where each α_l has its own presence rate at L_j.

Figure 1 illustrates an example, where flexible parameter is established based on membership function $\mu_E(z_l|w^*)$ for fuzzy generalized parametric sentence with 5 linguistic values: *bn*, *sn*, *z*, *sp*, *bp*. Each linguistic value corresponds to support value $z_1 = -0.8$, $z_2 = -0.4$, $z_3 = 0$, $z_4 = 0.4$, $z_5 = 0.8$. Labelled value for $w^* = -0.3$ from Fig. 1 reflects the situation, when *sn* has possibility $\mu_E(-0.4|-0.3) = 0.85$ to be in general parametric sentence, *z* has $\mu_E(0|-0.3) = 0.33$ and *bn* has $\mu_E(-0.8| - 0.3) = 0.04$. The rest linguistic variables are not in general sentence in this situation.

Therefore, flexible parameters allow soft switching between linguistic values, which are included into fuzzy generalized parametric sentence (5). Because of this, fuzzy rules, structure of which is changed depending on flexible parameters, may be constructed. To achieve this, each fuzzy elementary sentence $L_{a_j} : (x_{i-j} = \alpha_{r_j})$ from rth rule antecedent (3) should be changed by fuzzy generalized parametric sentence L_j (5) with specified flexible parameter w_j. Therefore, parametric antecedent representation $W_j = (w_1, w_2, ..., w_k)$ is obtained for

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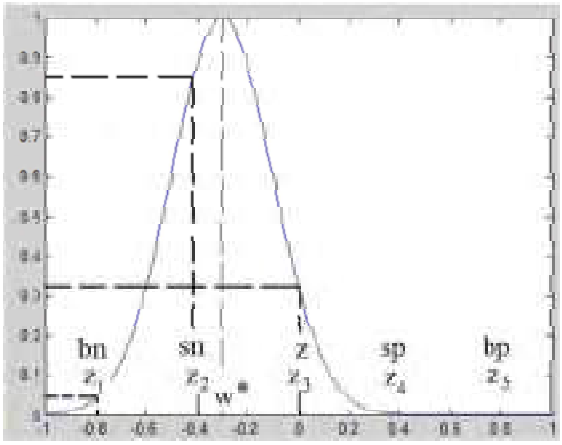


Fig. 1. Example with flexible parameter $w^* = -0.3$ for the TS model, which has 5 support values

rth rule. Truth value is computed for aggregated antecedent as t-norm of elementary truth values $J(L_j)$ for included parametric sentences L_j, which are calculated as in (6).

Fuzzy flexible TS model with N rules includes $N \times k$ flexible parameters, so the set of flexible parameters is N-by-k matrix, where each rth row corresponds to the vector of flexible parameters for rth rule.

Fuzzy inference based on flexible models is performed as in (4).

4 Immune Principle for Anomaly Detection Based on Flexible Models

In proposed system, objects for recognition are temporal patterns $(x_i, x_{i-1}, \ldots x_{i-k}) \subseteq S$ (S is initial time series). These patterns are objects, analysis of which allows to make a decision whether data contains anomalous (or pre-anomalous) samples or not.

Diagnosis system is considered as analogue of immune double-plasticity one. Input data is considered as antigen, flexible TS models are considered as antibodies. Here, TS models are constructed as double-plasticity models, which contain two sets of parameters: parameters of membership function for internal linguistic values and flexible parameters, which are responsible for structure changes of neuro-fuzzy net.

The work of diagnosis system is performed by the following scheme.

1. Initial models parameters and training parameters are defined. Human expert establishes training parameters and initial ones of the membership functions for linguistic values from TS model. Regarding to flexible parameters, they are chosen as support values $z_l (l = 1, 2, ..., m)$, which are evenly distributed at $W = [-1, +1]$.

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2. When new data (sample x_i or pattern $(x_{i-k}, x_{i-k+1}, ..., x_i)$) is obtained, adaptation is performed for flexible TS models via optimization of their parameters using prediction error for x_i.
3. Flexible parameters w_j are analyzed for significant changes. If at least one flexible parameter is changed higher than threshold $d = |z_l - z_{l-1}|$ $(l = 2, 3, ..., m)$ during training, then system confirms structure changes and anomalous statement, as well.
4. System returns to step 2.

If the above scheme is used for prediction, the following extended form should be used. Trend vectors referred to changes of flexible parameters during model training are included. The vectors store the changes occurred during k previous samples (k is established by human expert). Each iteration of the algorithm considers the changes behavior using trend vectors. If flexible parameter has monotonic change higher than $d/2$ $(d = |z_i - z_{i-1}|)$, then structure changes and pre-anomalous statement are confirmed.

It is clear that presented scheme and its extension for prediction are extremely common and can be specified depending on threshold, trend and "significant change" formalization.

5 Implementation Example

This section considers an example, which illustrates the anomaly detection based on described above scheme. Time series under consideration is generated by recurrent equations describing behavior of nonlinear dynamical system at discrete time interval $[t_0,\ t_{80}]$ (Fig. 2).

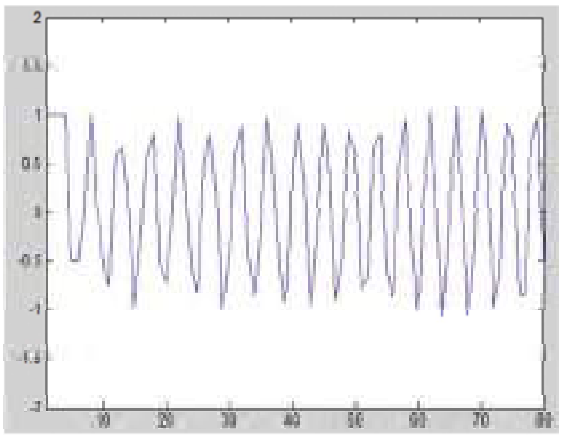


Fig. 2. Test time series

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Beginning from t_{40}, evolution law for the system is dramatically changed (it is considered as anomalous sample). It should be noted that this change is graphically invisible.

As an antibody, prediction model in form of fuzzy regression analysis is used:

$$x_t = c_1(t) \cdot x_{t-1} + c_2(t) \cdot x_{t-2} + c_3(t) \cdot x_{t-3} + c_4(t) \cdot x_{t-4} \tag{7}$$

Coefficients $c_j(t)$ are recomputed at each obtained time step t based on TS model training, which is performed as follows. To compute $c_j(t)$ ($j \in [1, 4]$), the fuzzy rule system is used:

$$\begin{cases} R_1\text{: IF } c_j(t-1) = bn \text{ THEN } c_j(t) = z_1 \\ R_2\text{: IF } c_j(t-1) = sn \text{ THEN } c_j(t) = z_2 \\ R_3\text{: IF } c_j(t-1) = z \text{ THEN } c_j(t) = z_3 \\ R_4\text{: IF } c_j(t-1) = sp \text{ THEN } c_j(t) = z_4 \\ R_5\text{: IF } c_j(t-1) = bp \text{ THEN } c_j(t) = z_5 \end{cases} \tag{8}$$

Here, coefficients c_j are referred to linguistic values $\alpha_1 = bn$, $\alpha_2 = sn$, $\alpha_3 = z$, $\alpha_4 = sp$, $\alpha_5 = bp$ (defined at $[-1, 1]$). Membership functions for the linguistic variables are illustrated in Fig. 3.

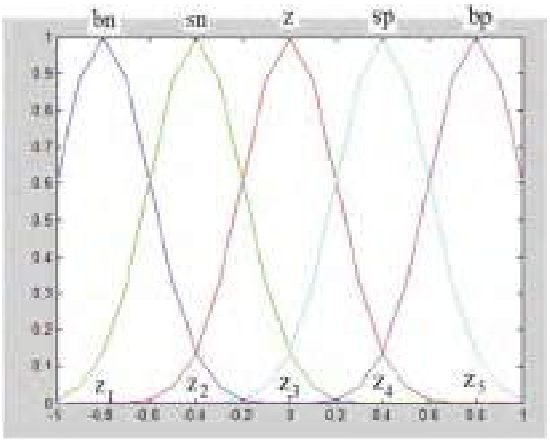


Fig. 3. Membership functions for used linguistic variables

Consequents of rules have the following support values: $z_1 = -0.8$, $z_2 = -0.4$, $z_3 = 0$, $z_4 = 0.4$, $z_5 = 0.8$. To obtain flexible TS model, let each antecedent be presented in form of fuzzy generalized parametric sentence with flexible parameter w_j:

$$L_l(w_j) : c_j(t-1) = bn|w_j \vee sn|w_j \vee z|w_j \vee sp|w_j \vee bp|w_j \tag{9}$$

As a result, fuzzy rules system is obtained for flexible TS model:

$$R_l : \text{IF } L_l(w_j) \text{ THEN } c_j(t) = z_l \qquad (l = 1, 2, ..., 5) \tag{10}$$

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Coefficient c_j is computed at time step t based on flexible TS model using fuzzy inference as follows:

$$c_j(t) = \frac{\sum_{l=1}^{5} J\big(L_l(w_j)\big) \cdot z_l}{\sum_{l=1}^{5} J\big(L_l(w_j)\big)} \tag{11}$$

where $J\big(L_l(w_j)\big)$ is the truth values for fuzzy parametric sentences (9), which are computed as

$$J(L_l|w_j) = \frac{\sum_{l=1}^{5} \mu_{\alpha_i}(c_j(t-1)) \cdot \mu_E(z_l|w_j)}{\sum_{l=1}^{5} \cdot \mu_E(z_l|w_j)} \tag{12}$$

In (12), membership function $\mu_E(x|w_j)$ is presented in Gauss form:

$$\mu_E(x|w_j) = \exp\big(-(x-w_j)^2/2 \cdot 0.1^2\big). \tag{13}$$

Algorithm of the work of the diagnosis system, which is based on the proposed model, is the following.

Coefficient values are initialized as $c_j(t) = 0$ $(j = 1,2,3,4; t = 1,2,3,4)$. When a new sample x_t $(t > 4)$ is obtained, new coefficients values are computed based on (11). Found values are substituted into (7) to predict $\hat{x}$ and square error $\epsilon = \big[x(t) - \hat{x}(t)\big]^2$ is computed. Vector W_j is adjusted according to minimization of prediction error.

Figure 4 illustrates flexible parameters changing during training for time series from Fig. 2.

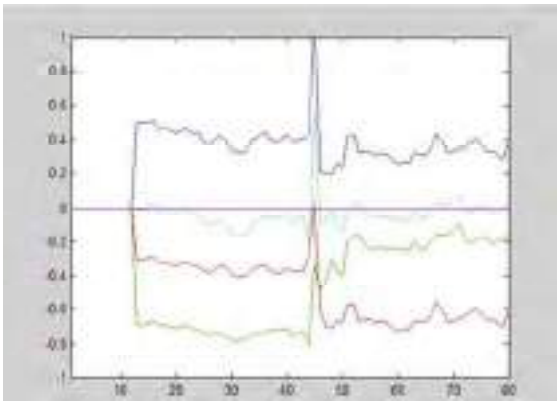


Fig. 4. Flexible parameters changing during training

Figure 4 illustratively shows saltatory change of parameters when anomalous presence (from x_{44} till x_{50}) is obtained. Flexible parameters are changed at $[t_{43}, t_{52}]$. In particular, $c_3(t)$ and $c_4(t)$ are changed between z and bn. Significant parametric changes illustrate structure changes of TS model. Based on structure changes, system sets anomalous statement. It should be noted that anomaly is almost invisible on initial time series.

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6 Conclusions

The task of anomaly detection and prediction is considered for continuous temporal data. A new solution, which is based on double-plasticity principles utilized by biological systems, is presented. Flexible neuro-fuzzy systems are used as immune antibodies. Significant difference of proposed approach from existing ones is in fact that anomaly detection is performed not directly by time series changes analysis. Anomalous presence is estimated by analysis of internal system structure, which changes are caused by external (or time series) changes.

Proposed approach is illustrated with the example of anomaly detection, where anomaly is graphically invisible.

The approach can be used as the basis of anomaly prediction technique based on trend analysis for TS model. Stable changes of flexible parameters from one support value to another shows anomalous evolution.

Proposed approach founds a new class of flexible fuzzy models, which assume soft parameters changing according to external actions due to specific flexible parameters. Fuzzy flexible models can be applied as a basis of the huge category of adaptive systems based on double-plasticity principles.

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