Hybrid artificial immune system approach for dynamical agent-based monitoring

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Abstract: The paper presents a new class of intellectual agent's models for artificial immune system with multi-agent platform. The fuzzy artificial immune system is used to design a general hybrid approach to monitoring system. The paper proposes multilevel structure of hybrid monitoring system with multi-agent cooperation and classification of fault event processing. On high level, artificial immune system produces agents, which are equipped with fuzzy classification algorithms. On low level, proposed system behave itself as fuzzy-dynamical system for registering and processing a sequence of fault events. The detailed structure and mathematical model of proposed fuzzy-dynamical system is developed. Fuzzy dynamical model of autonomous intelligent agent using nonlinear autoregression model is developed.
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1. Introduction

Systems monitoring usually based on monitoring the progress of deformation processes in controlled system parameter. Traditional monitoring methods require complex models of systems and contain systems of difference equations, but in many cases, such equations are difficult to obtain. For example, a wide class of life parameter monitoring systems exist, which is not be described with ordinary or partial difference equations. Moreover, when complex network system operates it is possible the structure of system is being changed. In accordance with this, if system has been described with difference equation system then it means we have no structure change, but only equation parameters. Obviously, it is not enough to get adequate model of system. Hence, it is difficult to apply widely known monitoring methods and there is a need to find brand new monitoring methods.

In this case, the solution is new monitoring methods using on artificial intelligence models. The possible methods belonging this area are artificial immune systems (AIS), which well suited for classification and identification incomplete and inexact monitoring data. This paper aims to use some elements artificial immune systems theory together with artificial multi-agent technologies and fuzzy-dynamical systems (FDS).

The area of AIS within artificial intelligence now is subject to intensive research and examination. Recently a sequence of original research methods related to above-mentioned area has been proposed. One of them is agent-based AIS approach for adaptive damage detection in distributed monitoring networks [1]. This method based on health monitoring network, which consists of group mobile software agents with pattern recognition programs. Adaptive resource management of mobile agents is performed over mobile sensor network deployed on proposed network framework. The basic principles distinguishing AIS among other biology-inspired information processing systems are: selective cloning dynamics of immune cells [2]; distributed classification and pattern recognition based on selective cloning [3]; clonal selection theory [4]; clonal selection algorithm for classification [5]; AIS abilities for data analysis [6] and so forth. Some recent surveys on AIS models and their applications are presented in [7, 8].

Methods and algorithms that have been cited do not limit applications of AIS. Immune system, being an example of unique system of natural monitoring, uses different immunological mechanisms for achievement of the remarkable properties among which the most important are the training and adaptation mechanisms implemented on the basis of the principles of distributed classification, identifications and image identifications by the means distributed in the organism. AIS is a new biology-inspired model useful for intrusion detection purposes [9-11]. The main features of human immune system, which consist in self and non-self cell discrimination are being transferred to AIS. Therefore, AIS suggests protection structure, which may be multilayered and used for prevention of multipurpose computer attacks. Trained intelligent software agents that cooperate with each other can detect each type of attack. Consequently, main ideas from AIS intrusion detection model may be adapted for monitoring systems if computer attacks play role as monitoring events.

However, there is an essential difference between computer attacks and monitoring events. One of differences consists that number of types of computer attacks significantly less than number of types of computer monitoring events. Then, one can make crisp identification of computer attack and do not make crisp identification of type of monitoring event except wide class to which it belongs. Fuzzy classification and FDS is necessary to distinguish events of monitoring. The rest of the paper is organized as follows. Section 2 presents general structure and principles of hybrid AIS approach to fuzzy dynamical model of monitoring system. Section 3 discusses new fuzzy dynamical model of agent-based monitoring system based on nonlinear autoregression model. We conclude the paper in section 4.

2. General hybrid approach to monitoring system

Monitoring of the distributed objects represents extremely complex task containing sets of poorly formalized factors. We name this method as "hybrid" because it consists of methods belonging AIS research area and fuzzy systems research area simultaneously. In the most general terms, it consists in observation over dynamics of response of controlled system under external factors, prediction of this dynamics, detection of critical signs of statuses, detection and identification of the abnormal events in monitoring data or essential deviations of system functioning from the normal. We propose framework as follows. We start from O – a set of monitoring operating modes, which consists of V and W – sets of normal and abnormal modes respectively. Obviously, the set O is formed by $O = V \cup W$. The task formulates as follows: we need to determine a set J that consists of decision rules, which identify normal and abnormal modes. Possible determination methods of set J elements are decision diagrams, expert system production rules and AIS related methods. However, use of only one immunological paradigm for a solution of the problem of monitoring of the distributed technical objects is not enough. At least, two main aspects support this fact and point of view. First of them is importance and effectiveness distributed calculation in aims of monitoring. Second, it is obvious that AIS presents itself a distributed system. These aspects are ground for intelligent multi-agent technologies.

Considering above-mentioned facts we intend to use two technologies, first is a fuzzy AIS based classification system and second is a multi-agent platform. Fuzzy AIS based classification system in fault monitoring context has been studied in several recent works [12–14]. Similarly to human immune system, AIS has to detect antigens, the foreign molecules from bacterium or other invaders. In this process there are two main white blood cells called T-cell and B-cell. The second of them, B-cells circulate the body in the blood and lymphatic vessels, produce antibodies and recognize foreign molecules called antigens. After the antigen interacts with antibodies, process of cloning of a lymphocyte is stimulated. The lymphocytes received because of cloning can slightly differ from the initial. Those lymphocytes, which are not interacting with antigens, gradually die off. Key characteristics of immunology are simulated mathematically [12-14] and can be therefore integrated into engineering systems. In our framework, monitoring agents simulate B-cells and their classification algorithms play role of antibodies. Vector of signs are used for coding of antigens. When monitoring event appears, the agent performs event registration and clones itself to increase detailed diagnosis specification. As result of cloning, agents cooperate with each other and transfer information about fault and diagnosis events. Figure 1 shows the block diagram of multilevel structure of proposed monitoring system.

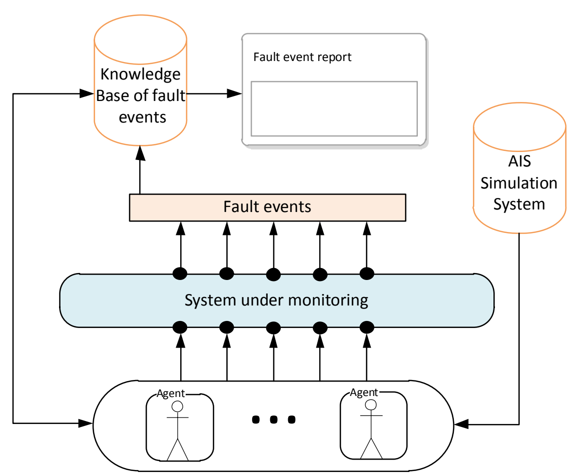

Figure 1. Block diagram of our proposed system.

AIS produces agents, which are equipped with fuzzy classification algorithms. After fault event was registered and agent did recognizing work the knowledge base makes a conclusion based on fuzzy logic rules. We propose that all agents together with knowledge base make the FDS.

Let us consider the FDS more detailed. Because monitoring process occurs in time, each of agents during a certain time interval Δt receives information about fault events from system under monitoring. Based on this information and using of knowledge base, agent predicts the dynamics of monitoring process and forms the shape of the process. Integral shape of process on completely observed time interval T allows making diagnosis solution. Thus, the main elements of FDS are procedures of shape calculation including fuzzy linguistics terms. Such linguistic terms may be as "low increase", "high decrease" and other similar diagnostic expressions. The neural network methods calculate the shape of diagnosis process as follows:

$$\begin{aligned} &X(t_0), X(t_1), \ldots, X(t_n) \Rightarrow \alpha(T), \beta(T), \ldots, \chi(T), \\ &Y(t_0), Y(t_1), \ldots, Y(t_n) \Rightarrow \alpha(T), \beta(T), \ldots, \chi(T), \\ &Z(t_0), Z(t_1), \ldots, Z(t_n) \Rightarrow \alpha(T), \beta(T), \ldots, \chi(T), \end{aligned} \quad (1)$$

where $X(t_i), Y(t_i), Z(t_i)$ are coordinates of monitoring process, α, β, χ are fuzzy terms, corresponding to coordinates, $i = 1, \ldots, n$.

In accordance with Sugeno fuzzy model [15] we can map (1) into sequence

$$\{X(t) = \alpha, Y(t) = \beta, \ldots, Z(t) = \chi\} \Rightarrow$$
$$\Rightarrow \{\Delta X(t) = c_1, \Delta Y(t) = c_2, \ldots, \Delta Z(t) = c_n\}, \quad (2)$$

where $X(t_i), Y(t_i), Z(t_i)$, α, β, χ are the same as in (1), $\Delta X(t), \Delta Y(t), \Delta Z(t)$ – increments of the coordinates, $c_1, c_2, \ldots, c_n$ – mapped numerical parameters.

For flexibility of proposed FDS, we consider fuzzy parameters instead of crisp numerical parameters c_i in (2). In order to distinguish those fuzzy parameters we denote as $\tilde{\Delta} X(t), \tilde{\Delta} Y(t), \tilde{\Delta} Z(t), \tilde{\Delta} t$, is an increment of single parameter, and $\tilde{\Delta}_\Sigma$ is summary parameters increment and so on, i.e with tildes. Such parameters can be received through fuzzification of crisp parameters. Figure 2 shows general model of fuzzy dynamical monitoring system. First step is fuzzification of input parameters $X(t), Y(t), Z(t)$ related with fuzzy rules $R_i : U_i \Rightarrow \Delta_i$ in knowledge base, where U_i – summary input of the described system. As result, we can determine true conditions of rules

$$J(U_i) = J[X(t) = \alpha] \& J[Y(t) = \beta] \& \ldots \& J[Z(t) = \chi], \quad (3)$$

where J – set of diagnosis decision rules.

Next step consists of reasoning about each rule R_i. It propagates true value from rule $J(U_i)$ in (3) to conclusion about Δ_i. Then we can determine the conclusion in vector form of sets of fuzzy increments as $\tilde{\Delta}_i = (\tilde{\Delta} X_i, \tilde{\Delta} Y_i, \ldots, \tilde{\Delta} Z_i)$. Further, we aggregate sets of rules into summary vector

$$\tilde{\Delta}_\Sigma = \left(\bigcup_i \tilde{\Delta} X_\Sigma, \bigcup_i \tilde{\Delta} Y_\Sigma, \ldots, \bigcup_i \tilde{\Delta} Z_\Sigma \right) \quad (4).$$

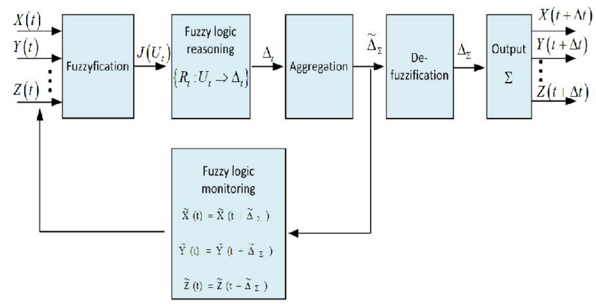

Figure 2. The structure of proposed fuzzy dynamical system

The last step is defuzzification (4) into vector Δ_Σ of crisp output values. We perform the defuzzification by widely-known "center of gravity" method [16] as

$$x^* = \frac{\sum_{x \in X} \mu_{\Sigma c(\bar{x})}(x) \cdot x}{\sum_{x \in X} \mu_{\Sigma c(\bar{x})}(x)} \quad (5).$$

3. Fuzzy dynamical model of agent-based monitoring system using nonlinear autoregression model

Autonomous agent is a key element of our proposed framework. The aim of this section is simulation of fault event sequence based on nonlinear time series. We observe time series denoted $S = (s(t_i) / i = 1, 2, \ldots)$, where elements accept values from a numerical set X and characterize fault events in i-th time points t_i. Model of the time series S can be represented in form of nonlinear autoregression:

$$S(t) = F(s(t-1), \ldots s(t-k)) + e(t), \quad (6)$$

where F – some unknown function, $e(t)$ – forecasting error, k – order of the model.

Autoregression (6) allows to model short-term dependencies among values of time series S. Because we consider long-term fault dependencies, the model (6) should be altered. For this purpose, we create on the basis of process S an aggregated process $s^i(t)$. This process is obtained by averaging of i-th values of time series S. Then we develop the autoregression model similar (6). However arguments of this model are not the k last members of a series S, but k values of aggregated processes $s^i(t)$. Thus, the model has the form

$$\hat{S}(t) = F(s(t-1), s^1(t-1), \ldots, s^k(t-1)) + e(t). \quad (7)$$

It is obvious that the function in (7) is nonlinear and we suggest using the fuzzy-logical model. We represent autoregression time series as FDS in previous section. Feedback inputs are obtained by aggregation of delayed values of time series S. The value of delay is k (that also means the order of the model) and output is forecasting value $s(t)$ at the time moment t. The rule base of FDS contains rules R_i in this form:

$$R_i : IF\ s(t-1) = \alpha_i \ \ and\ s^1(t-1) = \beta_i \ and \ \ldots and\ s^k(t-1) = \gamma_i \quad THEN\ s(t) = \omega_i ,$$

where $\alpha_i, \beta_j, \ldots, \omega_l$ – values of linguistic variable (fuzzy variable) are determined on numerical scale X, characterizing fault intensity; fuzzy variables $\alpha_i, \beta_j, \ldots,$ – input values and ω_l – output values of described FDS.

Let us consider $(k+1)$ phase space using for representation FDS. First k measurements correspond to input values of fuzzy-dynamical system and $(k+1)$ measurement correspond to its output at the time point t. Each rule R_i from knowledge base determines the fuzzy region $\tilde{R}$ at space U with a membership function:

$$\begin{aligned}&\mu_{Ri}(x_{i1}, x_{i2}, \ldots, x_{ik}, x_{ik+1}) = \\ &= \mu_{\alpha i}(x_{i1}) \,\&\, \mu_{\beta i}(x_{i2}) \,\&\, . \\ &\ldots \&\, \mu_{\gamma i}(x_{ik}) \,\&\, \mu_{\omega i}(x_{ik+1})\end{aligned} \tag{8}$$

For each specific set of input values $\bar{x}^* = (x^*_{i1}\, x^*_{i2} \ldots x^*_{ik})$ the function $\mu_{Ri}(x^*_{i1}, x^*_{i2}, \ldots, x^*_{ik}, x_{ik+1}) = \mu_{Ri}(\bar{x}^*, x_{ik+1})$ makes on a scale X the fuzzy set as FDS output, generated by the rule R_i. That is for each specific input vector $\bar{x}^*$ and output $x^* \in X$ membership function $\mu_{Ri}(\bar{x}^*, x^*)$ characterizes possibility of appearance x^* as predicted value of time series S in a time point t in case of the preset values of input variables $\bar{x}^* = (x^*_{i1}\, x^*_{i2} \ldots x^*_{ik})$ in the previous time points.

Obviously, input variables $\bar{x}^* = (x^*_{i1}\, x^*_{i2} \ldots x^*_{ik})$ accept numerical values. The membership function of an output fuzzy set can be rewritten in this form:

$$\begin{aligned}&\mu_{Ric}(x) = c \,\&\, \mu_{\omega i}(x) \\ &(c = \mu_{\alpha i}(x^*_{i1}) \,\&\, \mu_{\beta i}(x^*_{i2}) \,\&\, . \\ &\ldots \&\, \mu_{\gamma i}(x^*_{ik}),\ x \in X)\end{aligned} \tag{9}$$

The knowledge base of FDS includes an array of rules $\{R_i / i = 1, \ldots\}$. For output implementation we need to determine fuzzy area $\tilde{R}$ which includes all set of rules on space U. The area $\tilde{R}$ consists of a joint of the fuzzy areas corresponding to rules, related to the knowledge base of FDS. Membership function of the integrated fuzzy area has the form:

$$\begin{aligned}&\mu_{\Sigma}(x_{i1}, x_{i2}, \ldots, x_{ik}, x_{ik+1}) = \\ &= \bigvee_{Ri \in KB} \mu_{\alpha i}(x_{i1}) \,\&\, \mu_{\beta i}(x_{i2}) \,\&\, . \\ &\ldots \&\, \mu_{\gamma i}(x_{ik}) \,\&\, \mu_{\omega i}(x_{ik+1})\end{aligned} \tag{10}$$

By analogy, the membership function is determined by (10), for each specific array of input values $\bar{x}^* = (x^*_{i1}\, x^*_{i2} \ldots x^*_{ik})$ on a scale X. Taking into account (9) the membership function (10) is

$$\mu_{\Sigma c(\bar{x})}(x) = \bigvee_{Ri} c(\bar{x}) \,\&\, \mu_{\omega i}(x) \quad (x \in X). \tag{11}$$

Thus, expression (11) describes nonlinear function for the autoregression model provided by expression (6).

4. Conclusion

As result, the paper presents a new class of intellectual agents models for AIS multi-agent platform. This class of models makes a general framework for fault monitoring. Proposed models based on hybrid approach to FDS with AIS. Two new intellectual models of dynamic information processing in the conditions of inexact data are developed. Models allow solving fault-monitoring tasks.

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