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Analysis of Mechanical Equipment Failure Based on Improved AFSA-SVM

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Abstract

Aiming at problems in detecting mechanic equipment failure like large spatial dimension of data and inaccurate failure effect, etc., this paper proposes a failure detection model (AFSA-SVM) combining artificial fish swarm algorithm (AFSA) and supporting vector machine. Firstly, encode subset of network features into location of artificial fish while taking detection rate of 50% cross verification SVM training model as the standard to evaluate the featured subset, and then find the optimal subset through simulating foraging, clustering and following behaviors of fish swarm. Finally, SVM detects failures according to the optimal featured subset, and show through specific experimental data that algorithm in this paper simplifies the neutral network structure and improves speed of detecting failures while guaranteeing the accuracy of detecting failures.

Keywords*: AFSA, SVM, Mechanical failure*

1. Introduction

In the 1980s, the rapid development of artificial intelligence and computer technology, providing a new theoretical basis for fault diagnosis technologies, resulting in a fault diagnosis method based on knowledge. Fault address conducted a variety of research at home and abroad, Literature [1] an improved the Apriori algorithm, the fault map data to a 0-1 matrix, based on a matrix of pruning and dealing with frequent item-sets that calculate data, mining between the fault and the relationship between fault and operating parameters, provide strong support for device management. Given the feasibility of verification, Literature [2] proposed a surge voltage disturbance of power algorithm for mining equipment failure, reduced sensitivity to issues of data in the data collection and fault data similarity between class, and calculated between faults such similar characteristics. Compared with before the introduction, mining results more accurate and robust. [3] is a new algorithm for fault detection based on immune danger theory to enhance detection capabilities to potential malfunctions and the cumulative failures, experimental results show that the method has high detection efficiency and fault coverage, Literature [4] an improved Intelligent fault diagnosis method for decision tree. Results show that this method can effectively delete the redundant information, form a streamlining of decision-making rules, improving speed, with strong practicability. Literature [5] is based on momentum BP neural network algorithm for forecasting equipment state. Through e-learning and diagnostic lab show that momentum BP neural network algorithm can solve device failure prediction of nonlinear problems, and predictions are very accurate, high precision, fast convergence. Literature [6] presented an improved Ant Colony algorithm, combined with the binary property system and a system of multi-valued attributes, design adapted to the multi-valued attribute optimization of State transition rules and pheromone updating mechanisms. By comparison, proved its electronic system can solve many-valued sequence of optimization problems of the

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property system, expanded electronic system test optimization strategies to the value property. However, due to device structure and function improvement, equipment failure and failure characteristics of nonlinear characteristics are becoming increasingly complex, resulting in the modern fault diagnosis and identification difficulties and constantly improved. Just a theory, a method often cannot be achieved in a complex environment accurate and timely equipment fault diagnosis. So many theories and methods in one type of integrated intelligent fault diagnosis system of equipment fault diagnosis technology will be a new trend.

Based on the above researches, this paper proposes a failure detection model (AFDA-SVM) combining artificial fish swarm algorithm (AFSA) and supporting vector machine (SVM). Firstly, Firstly, encode subset of network features into location of artificial fish while taking detection rate of 50% cross verification SVM training model as the standard to evaluate the featured subset, and then find the optimal subset through simulating foraging, clustering and following behaviors of fish swarm.. Finally, SVM detects failures according to the optimal featured subset.

2. Improved Artificial Fish Swarm Algorithm

2.1. Basic Artificial Fish Swarm Algorithm

Artificial fish swarm algorithm (AFSA) imitates the foraging and following behaviors of fish swarms with strong search ability and fast search speed. Typical behaviors of fish swarms are as follows:

(1) Foraging behaviors. Suppose the current state of artificial fish swarm is Xi, and choose a state Xj at random within the scope of its vision. If the food density Yi<Yj, make one step forward towards this direction. Otherwise, choose the state Xj at random again to judge whether it meets the condition for progressing; after testing for nj times, if the condition for progressing can still not be met, then, move one step at random, the mathematical expression of which is:

$$\begin{cases} X_{i|next} = X_i + Rand() \cdot Step \cdot \dfrac{X_j - X_i}{\|X_j - X_i\|} & Y_i < Y_j \\ X_{i|next} = X_i + Rand() \cdot Step & otherwise \end{cases} \quad (1)$$

In the formula, Rand () is a random number within the scope (0,1), and Step is the length of pace.

(2) Clustering behaviors. Suppose the current status of artificial fish is Xi, the number of partners within the scope of vision is nf, and the central location is Xc. If Yc/nf>δYi, and δ is the density factor, it indicates that there is much food at the center of partners and it is not so crowded, then move one step forward towards the partner center, otherwise implement the foraging behavior, the mathematic expression of which is as follows:

$$\begin{cases} X_{i|next} = X_i + Rand() \cdot Step \cdot \dfrac{X_c - X_i}{\|X_c - X_i\|} & ,Y_c / n_f > \delta Y_i \\ findfood & otherwise \end{cases} \quad (2)$$

(3) Following behaviors. Suppose the current state of artificial fish swarm is Xi, and the location of artificial fish with the most density of food Yj with the scope of vision as Xmax. If Yj/nf> δ Yi, it shows that the partner Xmax has relatively higher density of food and it is not crowded in its surrounding, then, move one step forward towards the partner Xj, otherwise implement the foraging behavior.

$$\begin{cases} X_{i|next} = X_i + Rand() \cdot Step \cdot \dfrac{X_{\max} - X_i}{\|X_{\max} - X_i\|} & ,Y_{\max} / n_f > \delta Y_i \\ findfood & otherwise \end{cases} \quad (3)$$

(4) Random behavior. Artificial fish chooses a state at random within the scope of vision, and then move towards this direction, which belongs to the default behavior of foraging behavior.

(5) Bulletin. Bulletin is used to record the state of the optimal artificial fish.

AFSA is a random search algorithm, and for complex issues, it also has the defects like low efficiency at the later stage of searching and being easy to fall into local optimum, *etc*.

2.2. Improvement of Artificial Fish Swarm Algorithm

Chaos is a unique phenomenon in nonlinear dynamical systems with randomness, ergodicity and certainty, so introduction of chaos into AFSA can effectively avoid the algorithm at local minimum for a long time and improve the algorithm's global convergence and searching efficiency. Tent reflection of chaotic variable is:

$$x_{i+1}=\begin{cases}2x_i & x_i\in[0.\ \ 0.5]\\ 2(1-x_i) & x_i\in[0.5\ \ 1]\end{cases} \quad (4)$$

According to Tent reflection, artificial fish I produces chaos point column with feasible range according to the following steps:

(1) Reflect each dimension Xik,k=1,⋯,n of the artificial fish's state Xi into [0,1] according to formula (5)

$$cX_{ik}=\frac{(X_{ik}-a_k)}{(b_k-a_k)} \quad (5)$$

In the formula, a_k and b_k represent the minimum and maximum value of variable X_{ik} at the dimension k respectively.

(2) After iterating for M times, formula (5) produces chaos sequence $cX_{ik}^1, cX_{ik}^2, ..., cX_{ik}^M$.

(3) Reflect value of the chaos sequence's state into the initial space according to formula (6).

$$X_{ik}^s=a_k+cX_{ik}^s(b_k-a_k) \quad (6)$$

(4) Chaos point sequence of Xi after Tent reflection can be obtained from these chaos sequences:

s=1,…,M (7)

(5) Evaluate advantages and disadvantages of the state X_i^s of new artificial fish.

(6) If state X_i^s of the new artificial fish is superior to Xi, take as the results of local chaos research; otherwise, set s=s+1, and return to implement step (2).

Later in the AFSA optimization, artificial fish random behavior reduces optimized accuracy and efficiency, and feedback mechanisms. Define a feedback strategy for artificial fish behavior: artificial fish with some probability to the optimal state Billboard record swim, let the random behavior, artificial fish based on probability and with probability 1-p_{f0} perform feedback actions, optimize later to ensure the new algorithm can be better optimized accuracy and efficiency. And reduce p_{f0} according to formula (8)

$$p_{f0}=\theta p_{f0} \quad (8)$$

In the formula, θ is the recession factor of feedback probability.

3. AFSA-SVM Detection Model

3.1. Encoding Rules

For a given network with characteristics of m-dimensional data set D, feature selection is designed to select a target optimal feature subset of R, we use binary encoding rules, artificial fish location x values in binary representation of every dimension, taking the characteristics of selected as 1, and 0 otherwise.

3.2. Food Concentration

Food concentration is the basis to evaluate location of artificial fish, that is, standard to evaluate featured sub-set's performance, and two aspects are included in choosing target of intrusion features: ①higher rate to detect online intrusion; ②feature dimension at least as far as possible, the objective function (food densities) by the size of the selected subset of features and the detection rate is composed of two parts. Food concentration calculation formula is as follows:

$$FC = \lambda P_{error} + (1-\lambda)\frac{d}{D} \tag{9}$$

In the formula, d is the dimension of selected featured subset; D is intrusion detection feature original dimension; Perror represents a 5-fold cross-validation detection rate SVM training model; λ is the detection accuracy of the weighting factor.

3.3. Scope of Vision

If the field of view (Fv) is too small, prone to fish within Fv there are no artificial partners, random foraging probability is too large, leading to blindness enhanced search algorithm, but if Fv too, swarming behavior and increase the probability of rear-end behavior, not conducive to exploring new feasible solution space area. The studies indicate the degree of similarity between the two states by differences in the number of artificial fish status bits. If the similarity between two states with higher scores, it indicates less difference between the positions of the artificial fish. Artificial fish currently visible domain Fv position Xi is defined as:

$$F_v = \left\{ X_j \mid \sum_{k=1}^{L} \sigma_k \le \beta \right\} \tag{10}$$

In the formula, x_{ik} refers to the value of artificial fish at current location Xi and dimension k, $\sigma_k = \begin{cases} 1 & , x_{ik} = x_{jk} \\ 0, & x_{ik} \ne x_{jk} \end{cases}$, $\beta = 8$. (11)

3.4. Steps of AFSA-SVM Intrusion Detection

(1) Gather information about the network state and extract features of network state.

(2) Initialize parameters of artificial fish, mainly including location, movement pace Step, scale of population n, density factor δ, feedback probability Pfb, recession factor of feedback probability θ and the maximum iteration times max_iterate, *etc*.

(3) Generate n artificial fish at random with the feasible range and set the initial iteration times passed_iterate=0.

(4) Calculate the food concentration (FC) of individual of initial fish swarm at current location, an then rank them to choose the artificial fish individual with the most FC value into bulletin.

(5) Evaluate results of a certain artificial fish's foraging, following and clustering

behaviors. If a certain behavior is implemented, the state of artificial fish is superior to current state, the artificial fish moves one step forwards towards this direction and then turn to implement (8).

(6) Produce a random number r, and if r<Pfb, the artificial fish implements random behaviors; otherwise, implement the feedback behavior and move one step forwards towards the best direction in bulletin.

(7) Make chaos search towards the state of all the optimal artificial fish according to formula (5), (6) and (7) and get the best state of artificial fish within the current scope of solutions.

(8) Update the bulletin and record the best state of artificial fish obtained in (7) into bulletin.

(9) Update feedback probability according to formula (8).

(10) Judge the condition to end algorithm. If the maximum iteration time is met, end the algorithm and putout state of artificial fish on bulletin, that is, the optimal featured sub-set, otherwise passed_iterate=passed_iterate+1, and turn to implement (6).

(11) Simplify features of training set and detection set according to the optimal featured sub-set to get the simplified training set and detection set.

(12) Send training set with simplified features to SVM for training and establish network into equipment detection model.

4. Simulation Analysis

In this paper, 100 groups of data about failure of a local equipment maintenance center in Shaoxing are chosen and each group is divided into 50 sub-groups with the former 30 sub-groups for training and the rest 20 sub-groups for detection. Design one artificial vector machine classifier and choose three groups of data about failure of equipment as shown in Table 1, and get data as shown in Table 2 after the algorithm's processing.

Table 1. Failure Data of Three Groups

Group One	Group Two	Group Three
0.21	0.27	0.72
0.18	0.71	0.52
0.92	0.62	0.95
0.71	0.92	0.69
0.73	0.78	0.91
0.81	0.61	0.89
0.69	0.63	0.56
0.61	0.48	0.45
0.72	0.61	0.71
0.62	0.36	0.93
0.51	0.71	0.37
0.78	0.59	0.67

Table 2. Failure Date after AFSA-SVM Processing

Group One	Group Two	Group Three
3.5219	1.3568	1.6311
0.4218	0.1762	0.3749
0.3214	0.2523	0.6081
0.2725	0.0473	0.4176
0.0696	0.0656	0.4917
0.2743	0.3423	0.2551
0.3789	0.6141	0.3991
0.2964	0.5929	0.1605

It can be found in Table 1-2 that algorithm in this paper simplifies the structure of BP neural network and improve diagnosis speed after processing data of equipment failure samples, thus it is a feasible way to increase the real-time of BP neural network towards failure sample classification.

In order to further show the superiority of algorithm in this paper, compare algorithm in this paper and other detection algorithms in two aspects: detection error rate and detection and detection success rate. The results are as shown in Figure 1-2:

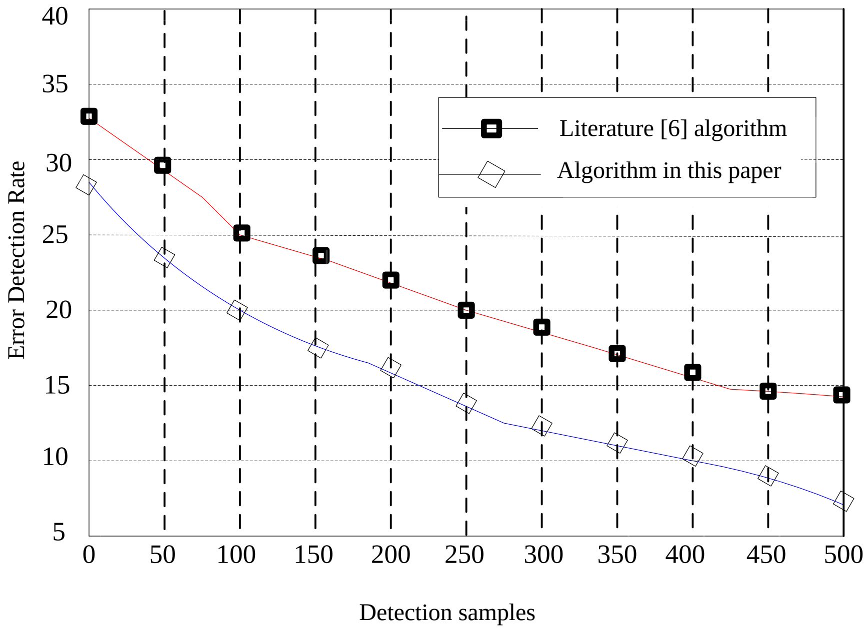

Figure 1. Comparison of Error Detection between Two Algorithms

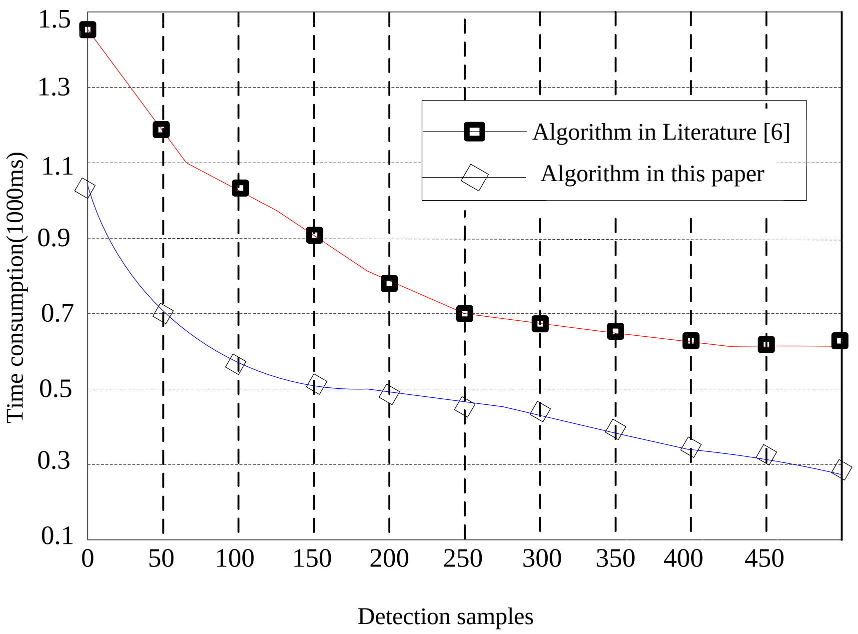

Figure 2. Comparison of Time Consumption between Two Algorithms

It can be seen from the above Figure 1-2 that algorithm in this paper is far superior to that in Literature [6] in terms of detecting errors, thus it effectively improves accuracy of detection, indicating algorithm in this paper has some certain advantages.

5. Conclusion

Aiming at the detection of mechanical failure control, this paper proposes a failure detection model (AFSA-SVM) combining artificial fish swarm algorithm (AFSA) and supporting vector machine (SVM). Firstly, encode subset of network features into location of artificial fish while taking detection rate of 50% cross verification SVM training model as the standard to evaluate the featured subset, and then find the optimal subset through simulating foraging, clustering and following behaviors of fish swarm. Finally, SVM detects failures according to the optimal featured subset, and show through specific experimental data that algorithm in this paper simplifies the neutral network structure and improves speed of detecting failures while guaranteeing the accuracy of detecting failures.

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