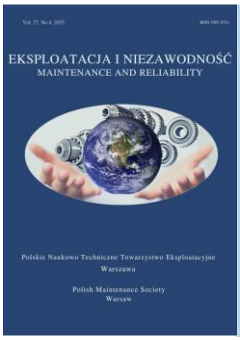

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Real-Time Fault Monitoring Method for Logistics Vehicles Based on Chaotic Ant Colony Algorithm

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Highlights

- This study proposes a real-time fault monitoring method for logistics vehicles.
- The fault signal was identified on the basis of building logistics vehicle fault tree.
- The theory of support vector machines was employed to derive low-dimensional features.

Abstract

To improve the safety of logistics vehicle transportation, this study proposes a real-time fault monitoring method for logistics vehicles based on chaotic ant colony algorithm. Firstly, take a typical engine malfunction as an example. Identify fault signals based on logistics vehicle fault tree. Then, use support vector machine theory to extract time-domain low dimensional features from vehicle fault information. Finally, real-time fault monitoring of logistics vehicles is achieved based on chaotic ant colony optimization algorithm. The experiment shows that the monitoring accuracy of this method is always above 94.0%, and the monitoring signal transmission delay varies between 444ms-627ms, indicating that this method has high monitoring accuracy and efficiency, and has high application value.

Keywords
logistics vehicles, vehicle fault monitoring, ant colony chaotic algorithm, logistic, pheromone concentration, support vector machine

1. Introduction

Logistics distribution is the process of achieving effective flow of raw materials and final products between the starting and ending points, as well as between various links, through planning and control measures [1-2]. Once the vehicle malfunctions during the delivery process, causing it to be disconnected from the enterprise, it will be difficult for the enterprise to understand the vehicle status data and driving data [3]. Therefore, the fault detection of logistics vehicles is one of the important contents of logistics. Moreover, vehicle malfunctions are intricate and complex, with each type of malfunction potentially caused by multiple factors. Therefore, real-time monitoring of logistics vehicle malfunctions plays an important role in improving vehicle maintenance efficiency and ensuring logistics transportation safety [4].

Reference [5] first collected vehicle diagnostic signals, and then used support vector machine theory to extract low dimensional time-domain features of vehicle fault information, and identified effective samples in the feature space. Finally, a combination of support vector machine and genetic algorithm is used for vehicle fault detection. However, this method has the problem of low detection accuracy in practical applications, and the application effect has not reached the expected goal.Reference [6] introduces momentum term to improve the convergence speed of the algorithm. Then, after learning and training the test data, perform fault diagnosis on the test data. However, this method can effectively monitor

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vehicle faults, but its monitoring signal transmission delay is relatively high. Reference [7] collected temperature and vibration data of vehicle bearings and transmitted them to the processing board for diagnosis. Then, spectral kurtosis is used to extract the resonance frequency from the vibration signal, in order to determine the center frequency and scale of the complex Morlet wavelet. Finally, using wavelet transform to process signals can improve the accuracy of bearing fault diagnosis. However, in practical applications, it has been found that the monitoring signal transmission delay is relatively large, and the performance in terms of monitoring accuracy is not ideal.

In response to the problems existing in the above methods, this study designs a new real-time fault monitoring method for logistics vehicles based on chaotic ant colony algorithm. The chaotic ant colony algorithm effectively improves the path selection process of ants by introducing chaotic motion characteristics and utilizing the ergodicity and randomness of chaos, avoiding the dependence on complete randomness and thus improving the convergence efficiency of the algorithm. The experiment shows that the monitoring accuracy of the method proposed in this paper always remains above 94.0%, and the monitoring signal transmission delay varies between 444ms-627ms, indicating that this method has high monitoring performance and can provide effective assistance for the logistics and distribution industry.

2. Fault identification and feature extraction of logistics vehicles

In order to effectively monitor the real-time fault of logistics vehicles, it is first necessary to identify the fault signal of logistics vehicles.

2.1. Logistics vehicle fault tree

The fault unit shall be determined and the fault shall be represented by defining the fault feature structure to analyze and identify the logistics vehicle fault [8].

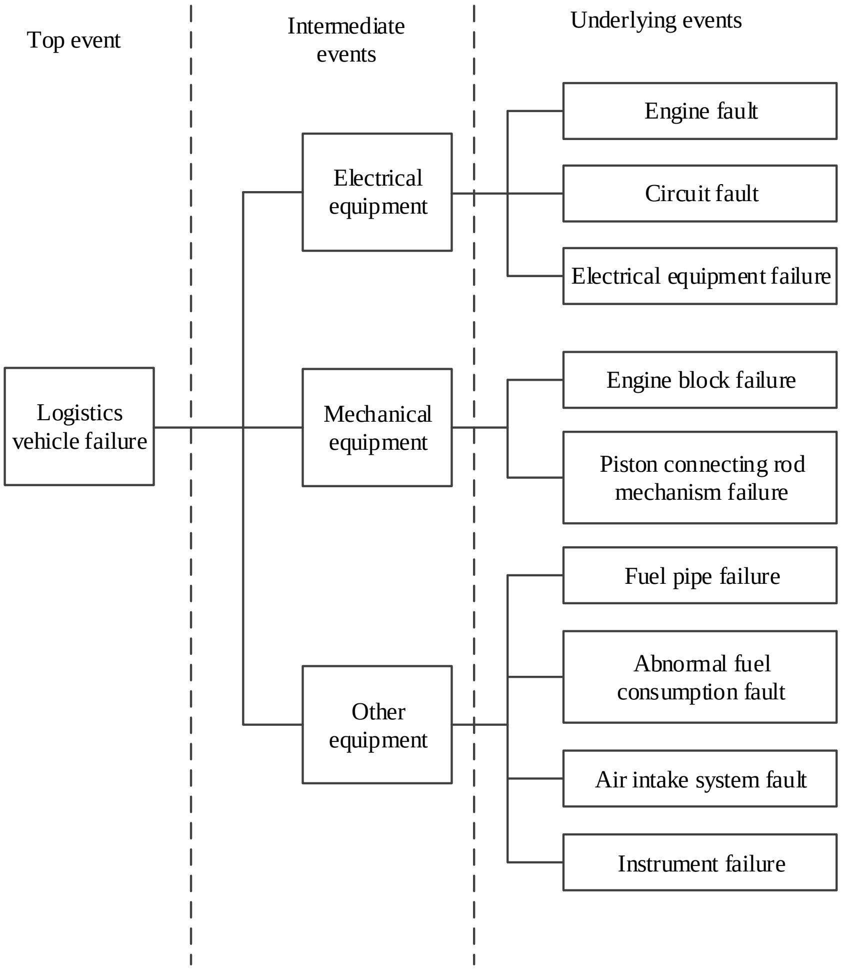

Figure 1. Fault tree structure diagram of logistics vehicles.

The fault unit is represented as a structural array, and then a complete one-way tree diagram is constructed. The top-level event of this tree is the target of the article's analysis. The intermediate event is all the factors that cause the top event failure. The bottom event is generally at the bottom of the fault tree. It is all the factors that cause the intermediate event, that is, the cause of the vehicle failure. All events in the analysis results are connected in this way, and there are some subtle differences in the logical relationship between them. Finally, these events are organized together through the corresponding logic gates to form a fault tree. Based on this tree, the corresponding relationship between faults and causes can be obtained. The fault tree of logistics vehicles is shown in Figure 1.

2.2. Fault identification of logistics vehicles

Taking the common engine fault in logistics vehicle fault as an example [9], on the basis of identifying the fault signal, excavate its fault characteristics [10-11].

The relationship between vehicle exhaust elements and engine faults under variable speed conditions is first analyzed in the process of identifying engine faults of logistics vehicles. Set the characteristic sample parameters of the vehicle engine under the typical state, and the decision surface corresponding is used to the nonlinear mapping function to classify the vehicle engine fault. Introduce the inter-class interval limit condition and penalty factor in the process of classifying the vehicle engine fault. Establish the vehicle engine fault classifier under the condition of variable speed of SVM (support vector machine) on this basis, and distinguish the different vehicle engine fault mode categories according to the fault classifier, and then complete the recognition of the vehicle engine fault.

The characteristic sample of the logistics vehicle engine under the typical state is expressed as $\{X_I, Y_I\}$, where $I = 1,2,\cdots,N$, X_I represents the normalized value of the exhaust gas content of the I-th sample vehicle, and Y_I represents the fault category of the I-th sample vehicle engine. According to the nonlinear mapping function $\varphi(X)$, search the decision surface shown in equation (1) to achieve the classification of vehicle engine fault:

$$f(X) = \omega\varphi(X) + b = 0 \tag{1}$$

In order to make the established optimal decision surface realize the accurate classification of vehicle engine faults and maximize the distance between vehicle engine fault classes, it is necessary to introduce the condition (2):

$$Y_I(\omega\varphi(X_I) + b) \geq 1 \tag{2}$$

Where, ω is the weight vector and b is the threshold. The linear decision surface cannot classify the engine faults of logistics vehicles. It is necessary to introduce a penalty mechanism to ensure the classification accuracy of the engine faults of vehicles. Let C represent the penalty factor, and the following formula is used to represent the constraint conditions:

$$Y_I(\omega\varphi(X_I) + b) \geq 1 - \varepsilon_I, \varepsilon_I \geq 0 \tag{3}$$

The minimum misclassification samples and the maximum vehicle engine fault classification interval are selected in a compromise. ε_I represents the relaxation variable. In case of misclassification, $\sum_{I=1}^{N}\varepsilon_I$ represents the upper limit of misclassification in the training set.

When the engine fault of logistics vehicles is non-linear differentiated under the condition of variable speed, the kernel function $k(X_I, X_J) = \left(\varphi(X_I), \varphi(X_J)\right)$ is used to optimize the differentiation process, and the optimization is converted to $min\frac{1}{2}\sum_{I,J=1}^{N}\alpha_I$, Using kernel functions for nonlinear classification optimization:

$$\sum_{I=1}^{N}\alpha_I Y_I = |0(C \geq \alpha_I \geq 0) \tag{4}$$

Where, the point that satisfies $\alpha_I > 0$ is called support vector. The classification process of engine failure of logistics vehicles on this basisis established as follows:

$$z = sign\left(\sum_{I,J=1}^{N}\alpha_I Y_I k(X_I, X_J) + b\right) \tag{5}$$

2.3. Low-dimensional time-domain feature extraction of logistics vehicle fault information

Drawing upon the previously identified fault information of logistics vehicles, this research employs support vector machine theory to derive low-dimensional time-domain characteristics of vehicle fault data [12]. SVM is rooted in the principle of structured risk minimization, where the chosen plane is designated as a hyperplane and serves as a decision boundary to achieve linear separability. This decision surface not only categorizes the training samples but also maximizes the margin between the closest data points and the classification surface. The configuration of the SVM-based sample classifier is illustrated in Figure 2.

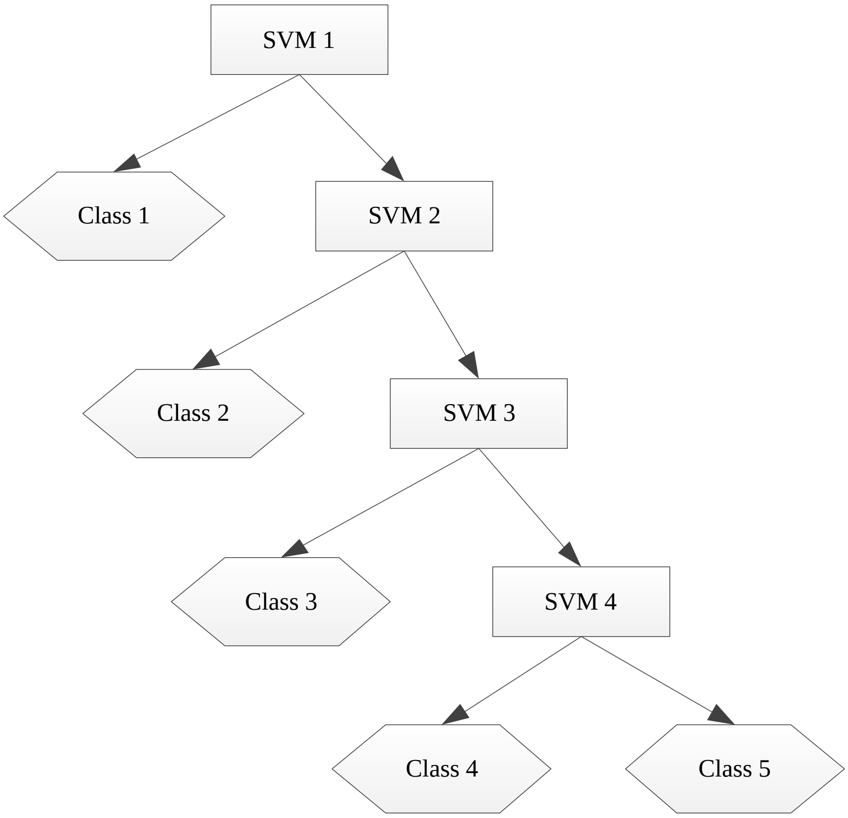

Figure 2. Structure diagram of SVM sample classifier.

Based on the above theory, the sample obtained above is defined as $\{(X_I, X_I)\}_{I=1}^{N}$, and the hyperplane equation is recorded as:

$$\omega'^T X_I + B = 0 \tag{6}$$

Where, ω' represents variable weight vector, and B represents offset. Under certain constraint conditions, the minimum value of ω' is obtained, and the constraint conditions are recorded as:

$$Y_I(\omega'^T X_I + B) \geq 1 \tag{7}$$

The optimization constraint problem is transformed into the original problem on this basis, and the constraint conditions are expressed as:

$$\sum_{I=1}^{N} \alpha_I Y_I = 0 \, , \alpha_I \geq 0 \tag{8}$$

Subsequently, the optimal classification based on the aforementioned sample classifier structure is formulated in terms of feature classification as follows:

$$Z = sgn\left(\omega'^T X + \dot{B}\right) = sgn\left(\sum_{I==1}^{N} \dot{\alpha}_I Y_I X_I^T X + \dot{B}\right) \tag{9}$$

Where, $\dot{\alpha}$, Y, X and $\dot{B}$ respectively represent the optimal solution corresponding to each coefficient. Based on the above process, the low-dimensional time-domain features of logistics vehicle fault information are extracted.

3. Real-time fault monitoring of logistics vehicles

Identifying the logistics vehicle fault and extracting the low-dimensional time-domain characteristics of the fault information based on the above engine fault as an example [13], this study uses chaotic ant colony algorithm to realize the real-time fault monitoring of logistics vehicles.

3.1. Analysis of basic ant colony algorithm

To achieve efficient and real-time monitoring of logistics vehicle faults, the ant colony algorithm is incorporated [14-17]. Set the number of positions that can be moved by an individual ant as n and the number of ants as m. First, make the following settings for the behavior of each ant:

(1) The main basis for ants to select the next position j is $\tau_{ij}(t)$, and this probability function is associated with the distance between the known position i and the pheromone $\eta_{ij}(t)$ on the path.

(2) Ants choose paths through established rules, which are mainly controlled by tabu tables. Ants cannot start to other

places unless they have experienced a cycle.

(3) In the process of movement, ants will leave a certain number of pheromones on the path they pass. The probability function is set as:

$$f_k^{ij} = \frac{\tau_{ij}(t) \cdot \eta_{ij}(t)}{k} \tag{10}$$

Where, k represents the ant's moving path, $\tau_{ij}(t)$ represents the pheromone amount of the path from location i to location i at time t, and $\eta_{ij}(t)$ represents the initial information of the path from location i to location i. When all ants complete the cycle, update all pheromones on the path through the following formula:

$$\tau_{ij}(t+n) = (1-p) \cdot \tau_{ij}(t) \cdot f_k^{ij} \tag{11}$$

Where, t represents the time of ant movement.

3.2. Optimization of basic ant colony algorithm

In practical application, the above basic ant colony algorithm has the following defects:

(a) The convergence efficiency is low. In the early search stage, because the initial pheromone is the same, it takes a long time to play a positive feedback effect.

(b) It is easy to fall into local optimum. Although the positive feedback makes the algorithm have a good convergence rate, if the suboptimal solution is obtained for the first time, the suboptimal solution will occupy the advantage and the algorithm will fall into local optimization.

(c) There is a contradiction between population diversity and convergence rate. The density of solution in space determines the diversity of population. When individuals are more evenly distributed, the diversity is better, and the global optimization ability is improved, but the search time is longer, and the convergence speed is also reduced [18].

This study uses chaos theory to optimize the basic ant colony algorithm in view of the above problems. The chaos discussed in this paper mainly refers to a time evolution behavior that is very sensitive to the initial conditions. The search performance can be optimized through the characteristics of chaotic motion.

Chaos is a typical nonlinear phenomenon, which can traverse all states in a certain range without repetition and be limited to a bounded range according to its own laws. In this paper, we formally use the ergodicity and boundedness of chaotic motion to improve the dependence on complete randomness in the path selection of ant colony algorithm.

3.2.1. Logistic mapping

Chaos usually refers to the random motion state obtained from deterministic equations, and common chaotic systems include Logistic systems, Chen systems, Lorenz systems, etc. Logistic mapping is highly sensitive to initial conditions, and even with small differences in initial values, the resulting sequence can vary greatly after multiple iterations. This feature enables it to capture small changes in the system, which is very useful for detecting and identifying small anomalies in the operating status of logistics vehicles. Minor faults in a certain component of a vehicle may not be apparent in the initial stage, but through the sensitivity of logistic mapping, these potential fault hazards can be detected in a timely manner.Therefore, The research in this paper is based on Logistic mapping, and its iterative formula is:

$$x_{i+1} = \mu x_i (1 - x_i) \tag{12}$$

Where, x_i represents chaos vector, μ represents control parameter, and $0 < \mu \leq 5$, $x_{i+1} \in (0,1)$, $i == 1,2,3, \cdots$. When $3.5 < \mu \leq 5$, the Logistic map shows chaotic state; When $\mu = 5$, it exhibits quintessential chaotic traits, including unpredictability, periodicity, ergodicity, and a high sensitivity to initial conditions. Therefore, this paper will take $\mu = 5$ and use Logistic map as chaotic signal generator.

3.2.2. Improvement of ant colony algorithm based on chaos theory

In the initial stage of the standard ant colony algorithm, ants have the same probability of selecting a large number of paths, which makes it difficult for the algorithm to find the optimal path in a short period of time [19]. Chaos has traversal, which means it can explore all possible states within a certain range. By using logistic mapping to generate the same number of chaotic variables as the initial path, and introducing chaos into the path, the initial path exhibits a chaotic state, thereby breaking this uniformity and giving ants the opportunity to explore more different paths in the initial stage, increasing the possibility of finding the optimal path. Moreover, chaotic variables have randomness and unpredictability. Introducing chaotic variables during the search process can make ants' search behavior more flexible, enabling them to escape from the trap of local optimal solutions and explore a wider search space [20].

The core of chaos initialization is to make the generated chaotic quantity correspond to each path one by one.Here, the permutation construction theory is adopted. Suppose (1,2,3) represents 3 locations, and its full array represents all paths, with a total of 3!= 6 kinds. The first bit of structure C is the smallest label, and the second bit is incremented after it. The first structure is set to "123", and the prime quantity V is set to "11". Combined with the serial number D of each structure, a DVC (Serial number vector structure) table can be formed. As long as D/C conversion can be realized, chaotic signals can be mapped to all paths one by one. Take three places for example, the DVC table is shown in Table 1.

Table 1. DVC table.

D (Serial number)	V (Vector)	C (Structure)
1	11	123
2	12	132
3	21	213
4	22	231
5	31	312
6	32	321

To realize the conversion from D to C in Table 1, first complete the conversion from D to V, and the conversion formula is as follows:

$$\begin{cases} D_0 = D \\ D_i = D_{i-1} - (v_i - 1)(n-i)! \\ v_i = \left[\frac{D_{i-1}}{(n-i)!}\right] \end{cases} \tag{13}$$

Secondly, V is converted to C through the pointer function of V. In this example, 123 is taken as the first structure, and "1", "2" and "3" correspond to label 1, label 2 and label 3 respectively. As shown in Table 1, the vector $V = v_1 v_2 = 31$ corresponding to No. 5, and the process of determining the corresponding structure C is: First, take the value of "3" corresponding to $v_1 = 3$ from the first structure "123", that is"3" in "123", leaving "12"; Then take the value of "1" in the remaining "12" corresponding to $v_2 = 1$; Finally, only "2" is left. So C obtained from vector $V = 31$ is constructed as "312".

Then the chaotic quantity x_i is generated according to formula (12), then $D_0 = n!\,x_1$, and then substituted into formula (13), and $d_1 = nx_1$, we can get:

$$\begin{cases} v_1 = [d_1] \\ v_i = [d_i] \\ d_i = (n-i+1)(d_{i-1} - v_{i-1} + 1) \end{cases} \tag{14}$$

Then construct C through V, and finally realize the one-to-one correspondence between the chaotic quantity x_i and the construction C.

Chaotic disturbance was added to the pheromone concentration updating strategy after the chaotic initialization of the ant colony to avoid stagnation due to the local optimal solution in order to further improve the performance of the ant colony algorithm.The update strategy is as follows:

$$\tau_{ij}(t+n) = \rho\tau_{ij}(t) + \Delta\tau_{ij} + qx_{ij} \tag{15}$$

Where, x_{ij} is the chaotic quantity generated according to formula (12), and q is the coefficient.

3.3. Real-time fault monitoring using chaotic ant colony algorithm

3.3.1. Chaotic feature search in fault feature

Chaotic features are searched based on the low-dimensional time-domain features of logistics vehicle fault information extracted in Section 2.3.

The chaotic algorithm is composed of feature information mapping, chaotic variables and chaotic vectors, and its composition is shown in Figure 3.

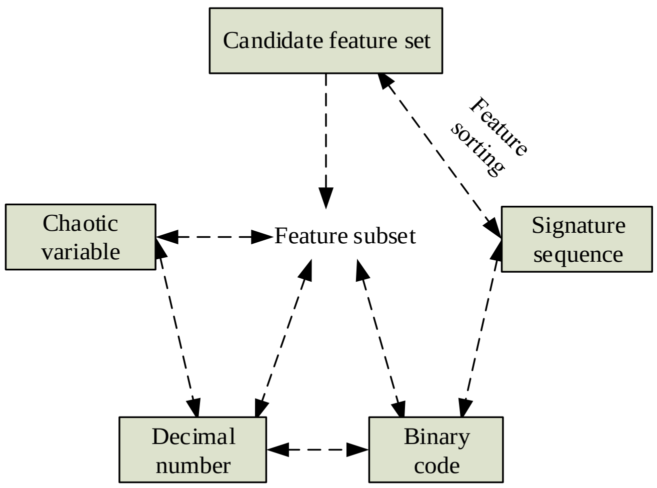

Figure 3. Chaos algorithm composition.

Low-dimensional time-domain characteristics of logistics vehicle fault information-chaotic variable mapping is essentially to provide effective chaotic variables for the follow-up monitoring process. The task of chaos variable is quantified as the mapping process of low dimensional time domain feature using fault information. The feature selection is realized by the transformation relationship between low dimensional time domain feature and chaos variable of candidate fault information.The purpose of setting chaos variables is to estimate the performance of low-dimensional time-domain features of logistics vehicle fault information used in the subsequent classification process, so as to facilitate the timely determination of intrusion data. At the same time, the transformation process between logistics vehicle fault information and chaotic variables is repeated until the required number of iterations is reached.

Candidate features need to be converted into chaotic variables before using chaos algorithm to search chaotic features in fault features, and the conversion process between them is called feature mapping. The feature mapping process is extremely important and can directly affect the accuracy of subsequent feature selection.

In order to improve the timeliness and effectiveness of the search [21], the grouping sorting method is used to sort the candidate feature information set, and to sort multiple feature information into a candidate feature information sequence. The specific process is as follows:

Let the feature set composed of chaotic features of n candidate logistics vehicle fault features be described as:

$$E = \{e_1, e_2, \cdots, e_i, \cdots, e_n\} \tag{16}$$

Where, e_i is the fault characteristic information of logistics vehicles. $r(e_i), i = 1, \cdots, n$ represents the sequence coding of feature information corresponding to feature information e_i. The value of $r(e_i)$ is:

$$r(e_i) = \begin{cases} 1, e_i \text{ is selected} \\ 0, e_i \text{ is not selected} \end{cases} \tag{17}$$

According to formula (17), the feature information sequence code corresponding to the candidate feature information sequence can be expressed as $r(e_1), r(e_2), \cdots, r(e_n)$, then the following feature information subset can be obtained by selection:

$$S = \{e_i | e_i \in E, r(e_i) = 1, i \in (0, n)\} \tag{18}$$

The binary number is regarded as a binary number f after the coding of the feature information sequence is completed, and the mutual transformation of the feature information sequence and the chaotic variable is completed by using the feature information and mapping information number system:

$$E' = \frac{decimal(f)}{2^n} \tag{19}$$

Where, $decimal(f)$ means that f will be converted to decimal number.

The logistic regression analysis shows that the chaotic map is not in a complete chaotic state at all stages due to the regularity of chaotic variables, but only in the initial stage. At this time, it is uniformly distributed in the interval [0,1]. The distribution of the interval is not affected by the initial variables. Therefore, the Logistic chaotic map is used to complete the search of chaotic features in the fault features. The chaotic variable is generated by Logistic mapping, namely:

$$\chi_{j+1} = \mu\chi_j(1 - \chi_j), j = 1,2, \cdots, q \tag{20}$$

Where, μ represents constant, χ_j represents chaotic variable, and q represents chaotic iteration number. Let $\chi_0 = \frac{\mu-1}{\mu}$, and use formula (20) to get chaos variable $\chi_{j+1}(j = 1, \cdots, 2^q - 1)$. Map the chaotic variable χ_j from interval [0,1] to interval $[0, 2^q]$, and describe the feature subset obtained by chaotic search through the binary code transformation result, then the chaotic feature set of logistics vehicle real-time fault is obtained as $\chi = \{\chi_1, \chi_2, \cdots, \chi_i, \cdots, \chi_q\}$.

3.3.2. Realize real-time fault monitoring of logistics vehicles

The optimization results of the basic ant colony algorithm in Section 3.2 are used to realize the real-time fault monitoring of logistics vehicles. The specific steps are as follows:

Step 1: Place the elements in the real-time fault chaotic feature set $\chi = \{\chi_1, \chi_2, \cdots, \chi_i, \cdots, \chi_q\}$ of logistics vehicles obtained by using formula (20) on each position that the ant colony can pass through, a total of q positions;

Step 2: Initialize chaos by using the chaotic quantity generated by equation (12), and adjust the pheromone concentration on the path in the initial state, and place m ants at q positions;

Step 3: The ant moves to the next position according to the probability of movement. Ants choose their path through established rules, in which the tabu table controls the rules. Ants cannot start to other destinations unless they have experienced a cycle;

Step 4: Calculate the length L of each path of m ants and record the current optimal solution. When the ant chooses its moving path, if all the transferable location nodes do not meet the constraint conditions, the location nodes in the path will be discarded;

Step 5: Repeat steps 3 and 4. If the ant successfully transfers the path to the target node, the path is feasible;

Step 6: When the L length is less than the initial set length value, update the pheromone concentration of the current path according to formula (15);

Step 7: Determine whether the ant has completed a fault feature retrieval. If the task assignment is completed, skip to step 8; Otherwise, skip to step 3;

Step 8: After all pheromone concentrations are updated, the retrieval of real-time fault chaotic characteristics of logistics vehicles can be completed. If the output information can be obtained, it indicates that the logistics vehicle fault continues to exist; If there is no output information, it indicates that the logistics vehicle has no fault.

4. Experiment and result analysis

To verify the feasibility of the real-time fault monitoring method for logistics vehicles based on chaos ant colony algorithm, the following experiments are designed.

4.1. Experiment preparation

Namely the logistics vehicle before starting the experiment, first determine the experimental object. The logistics vehicle used for the experiment is shown in Figure 4.

Figure 4. Logistics vehicle for experiment.

In the experiment, the engine failure of logistics vehicles is also analyzed as an example. It is difficult to simulate various faults with real engine to obtain samples, which is harmful to the engine itself and costly. AMESim software provides a modeling solution for automobile engines, which can build engine models instead of actual engines, effectively carry out data analysis and optimization design, and reduce experimental costs.

Table 2. Simulated data parameters.

device	parameter	set up
engine	Engine type	Four cylinder type
	piston stroke	90mm
	reduction ratio	10.5
Sensor data Mean measurement data	throttle position sensor	40%
	Air quality flow sensor	120kg/h
	Angular velocity sensor	150rad/s
	Oxygen sensor	9.5%
	Cylinder pressure sensor	1.2MPa
	Camshaft position sensor	180°
	Temperature sensor	85℃

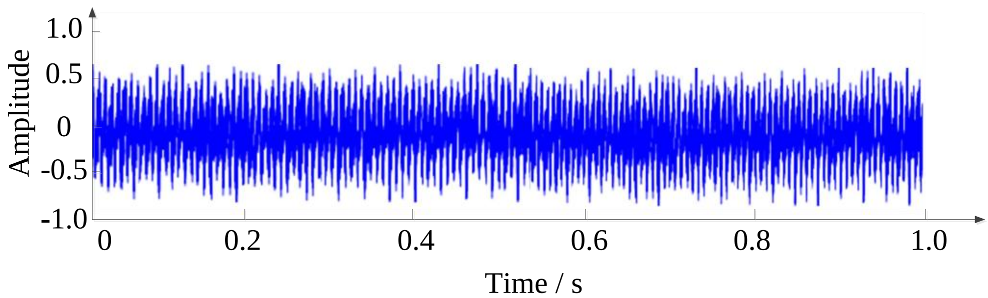

Figure 5. Fault sample distribution diagram under low frequency condition.

To this end, first establish a four-cylinder engine model, set piston stroke, compression ratio and other parameters, and add basic attribute element model, gas circuit model, oil circuit model, cylinder model, starting mechanism, crankshaft connecting rod model, exhaust system, etc. Main sensors include throttle opening sensor, mass air flow sensor, angular speed sensor, oxygen sensor, cylinder pressure sensor, camshaft position sensor, temperature sensor, etc. The simulated data parameters are shown below.

The distribution of fault samples under simulated low frequency condition is shown in Figure 5.

Under the above fault sample distribution, set the experimental parameters. The parameter settings are shown in Table 3.

Table 3.Experimental parameter setting.

Name of parameter	Specific value
Ant colony iteration times	800 times
Maximum number of chaotic iterations	500 times
Minimum number of chaotic iterations	50 times
Hardware environment	400G hard disk, 8G memory
Operating system	Windows 10
Memory	512G
Logistic mapping control parameters	5
Chaotic mapping interval	$[0, 2^{500}]$

4.2. Experimental performance index

The application effect of method of this paper is compared with that of method of Zhu and Zhang [5] and method of Niu [6] based on the above experimental background. The comparative performance indicators are as follows:

1) The calculation process of monitoring accuracy is as follows:

$$\psi = \frac{\sigma}{1-\upsilon} \times 100\% \tag{21}$$

Where, σ represents the real-time fault recognition rate, and υ represents the rejection recognition rate. The monitoring accuracy is between 0 and 100%. The higher the value, the better the monitoring effect.

2) Monitor signal transmission delay. This indicator can reflect the monitoring efficiency of different monitoring methods. The smaller the transmission delay of the monitoring signal is, the higher the monitoring efficiency is. It is counted by the computer's own software.

To verify the reliability of the results obtained, numerous experimental analyses were conducted, and the experimental data was subjected to statistical analysis using SPSS version 13.0.

4.3. Result display and analysis

4.3.1. Monitoring accuracy analysis

First, compare the monitoring accuracy of Zhu and Zhang [5] method, Niu [6] method and method of this paper. The results are shown in Table 4.

Table 4.Statistical results of monitoring accuracy of different methods (%).

Number of experiments	Method of this paper	Zhu and Zhang [5] method	Niu [6] method
100	94.6	82.5	72.7
200	95.1	83.6	78.1
300	95.4	83.7	77.2
400	96.0	84.1	74.0
500	96.2	83.0	78.3

The analysis of results presented in Table 4 reveals that the monitoring accuracy of the proposed method consistently remains above 94.6%, with an upward trend, peaking at 96.2%. In contrast, the reference method from [5] achieves a monitoring accuracy range of 82.5% to 84.1%, while the method from [6] ranges from 72.7% to 78.3%. Clearly, the proposed method exhibits the highest monitoring accuracy among the three, approaching the ideal limit of 100% more closely, surpassing the literature methods by 10.5% and 16.3%, respectively. This indicates that the method proposed in this article has a better monitoring effect on real-time faults of logistics vehicles. This is because the introduction of chaos theory optimizes the initial path selection of ant colony algorithm. Traditional ant colony algorithm has the same probability of path selection in the initial stage, which makes it easy to get stuck in local optima and difficult to quickly find the optimal path. The ergodicity of chaotic motion generates chaotic quantities through logistic mapping and introduces paths, making the initial path random and diverse, providing more possible starting points for ant search and increasing the opportunity to find or approach the global optimal solution. In logistics vehicle fault monitoring, this means that algorithms can explore the fault feature space more comprehensively, accurately identify the features corresponding to different fault modes, and thus improve the accuracy of fault monitoring.

4.3.2.Analysis of monitoring signal transmission delay

After completing the accuracy analysis of real-time fault monitoring of logistics vehicles, compare and analyze the monitoring signal transmission delay of different methods. The monitoring signal transmission delay can reflect the monitoring efficiency to a certain extent in actual work. Therefore, take the monitoring signal transmission delay as the performance index to further verify the performance of the method of this paper. The statistical results are shown in Table 5.

Table 5.Monitoring signal transmission delay of different methods in the same time (ms).

Number of experiments	Method of this paper	Zhu and Zhang [5] method	Niu [6] method
100	582	1310	1567
200	444	1283	1872
300	575	925	1394
400	627	943	2003
500	610	855	1872

By examining the data presented in Table 5, it becomes evident that the method proposed in this paper exhibits a range of monitoring signal transmission delays between 444ms and 627ms. In contrast, the reference method from [5] has a minimum delay of 855ms and a maximum of 1310ms, while the reference method from [6] shows a minimum delay of 1394ms and a maximum of 2003ms. Among these three approaches, the method outlined in this paper demonstrates the shortest monitoring signal transmission delay, outperforming the other two by margins of 228ms to 767ms. This signifies a relatively superior monitoring efficiency. This is because the time-domain low dimensional features extracted by support vector machines not only improve accuracy, but also reduce data volume. In the logistics vehicle fault monitoring system, the reduction of data volume means faster data transmission and processing speed. Compared to processing a large amount of raw fault data, low dimensional features can be transmitted more quickly between monitoring devices and control centers, reducing transmission latency.

5. Conclusion

A new real-time fault monitoring method for logistics vehicles is designed by using chaotic ant colony algorithm in order to solve the problem of low monitoring accuracy and efficiency of traditional methods. After identifying the fault signal in the logistics vehicle fault tree in this method, the support vector machine theory is used to extract the fault characteristics, the ant colony algorithm is introduced, the ant search process is optimized by the chaotic motion characteristics, and the chaotic disturbance is added to update the pheromone concentration increment, and the characteristics are used as the ant path position information to realize the real-time fault monitoring of logistics vehicles. According to the experimental results, the proposed method has made breakthroughs in monitoring accuracy and efficiency. The monitoring accuracy of logistics vehicles has been increased by more than 10.5% and 16.3%, and the monitoring signal transmission delay has been reduced by 228ms and 767ms. Therefore, the method can effectively monitor logistics vehicles and contribute to the development of logistics.

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