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Comparison of methods for reducing fault characteristics of industrial robot actuators

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Abstract

Actuators are one of the core components of industrial robots, which are directly related to the reliability of industrial robot systems. The ability to reasonably reduce the fault characteristics of industrial robot actuators has important engineering practical significance for improving the correct rate of fault diagnosis. This paper proposes a method of minimum distance within a category, the core of which is to select the minimum mean value of the distance within a category of the same fault feature under the premise of eliminating the influence of dimensions, to improve the clustering effect of similar features. The step is to extract the feature with the smallest mean value of the distance within the class, and then repeat the above steps to extract the feature from the remaining features. This process improves the efficiency of reduction and reduces the amount of calculation. The method is applied to the fault feature reduction of industrial robot actuators, and compared with the typical feature reduction method. The experimental results show that the reduction method proposed in this paper has a faster calculation speed than the sequential backward selection method. The principal component analysis method has a better clustering effect. At the same time, this method also provides a new idea for feature reduction methods in the field of fault diagnosis.

Keywords

Feature reduction fault diagnosis industrial robot PCA.

1. Introduction

In the field of industrial robot fault diagnosis, in order to ensure the integrity of the information, as many feature parameters as possible are extracted [1-2]. However, extracting too many feature parameters has the following problems: it takes up a lot of resources, resulting in low efficiency, which is not conducive to online monitoring from time to time. There may be information overlap, redundancy or even errors between different characteristic parameters, which increases the difficulty of diagnosis. Therefore, in order to improve the accuracy and efficiency of fault diagnosis and meet the timeliness requirements of fault diagnosis online detection, it is necessary to adopt the feature reduction method. Its purpose is to eliminate redundant, interference and even wrong features. Obtain more reliable and necessary features and reduce the complexity of diagnosis. Simplify feature dimensions to improve the speed and accuracy of fault diagnosis.

The basic idea of feature reduction is to reduce feature parameters through the calculation of functional functions [3-4]. Or through a transformation matrix, the data set in the high-dimensional space is mapped to the low-dimensional space. However, the reduced parameters or the data mapped to the low-dimensional space can represent the original data set. At present, the commonly used feature reduction methods for fault diagnosis of industrial robots are sequential backward selection method and principal component analysis method. The advantage of the sequence backward selection method is that it is very logical and intuitive, but the data of different parameters are quite different, so constructing the minimum function is the key [5]. The advantage of the principal component analysis method is that the order of selecting principal components can be determined by the cumulative contribution rate, which reduces the calculation workload, but the meaning of principal components is not as clear and clear as the original variables, and the interpretability is poor [6].

This paper takes industrial robot actuators as the research object. Aiming at the shortcomings of the current feature reduction methods, a reduction algorithm with the mean value of the intra-class distance is proposed (referred to as the intra-class distance minimization method). This method improves the clustering effect of similar features by selecting the minimum mean value of the intra-class distance of the same fault feature, and effectively provides the correct rate of fault diagnosis. At the same time, it has a smaller amount of calculation, which improves the speed of calculation and facilitates real-time fault monitoring. It has important engineering application value.

2. Feature reduction model

The sequence backward selection method is a method of directly reducing feature parameters. The basic idea is: in the k-th step, subset $V_{k,i}$ is selected by calculating the importance of the function function, and subset $V_{k,i}$ is obtained by subspace V_{k-1} removing the parameter P_i. which is:

$$V_{k-1} \supset V_{k,i} = \{V_{k-1} - P_i\} \tag{1}$$

In the same way, the subspace V_k is also obtained by repeating the above steps. At this time, the smallest function is selected, namely:

$$F(V_k) = \frac{1}{J(V_k)} = \frac{1}{\underset{i=1,d-k}{Max}\left[J(V_{k,i})\right]} \tag{2}$$

Figure 1 shows the steps of applying the sequential backward selection method from 5 features to 2 features:

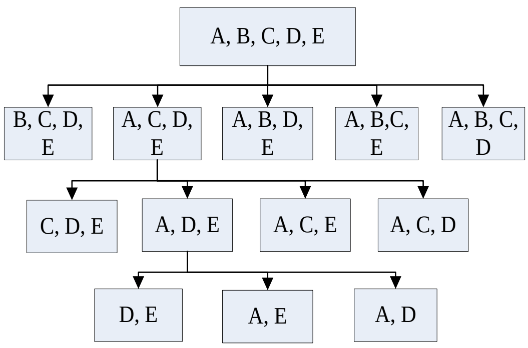

Figure 1 Schematic diagram of feature reduction of sequence backward selection method

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The advantage of the sequence backward selection method is that it is very logical and intuitive. Each time the algorithm selects the smallest item of the function function, one feature can be eliminated, and the sequence will be gradually narrowed down. Different parameter data are quite different, so constructing the minimum function is the key, and the reduction rule is also one of the difficulties.

When there are many parameters, this reduction method requires a large amount of calculation, because each parameter needs to be reduced step by step through an algorithm. Assuming that there are a total of N parameters, when it is reduced to 1 parameter, it needs to be calculated $N(N-1)/2$ again. And need a comparison $N(N-1)/2$.

Principal component analysis (PCA) is a common feature reduction method that has been applied in many fields. The basic idea is to map data to a new projection space through orthogonal transformation, where the direction of data mapping is the maximum variance. The specific steps are as follows:

Hypothetical data set $A=\{a_1,a_2,...,a_n\}$, and $A\subset R^{m\times n}$, Indicates that each vector has m samples. Data set $B=\{a_1,a_2,...,a_n\}^T=\{b_1,b_2,...,b_m\}$, and $B\subset R^{n\times m}$.

(1) Standardized processing:

$$x_i=\frac{B-\mu}{S} \tag{3}$$

Among them, μ and S respectively represent the mean and standard deviation of all samples of the i -th index, and

$$\mu=\frac{1}{m}\sum_{\mathrm{i=1}}^{\mathrm{m}} b_i \tag{4}$$

$$\sigma=\sqrt{\frac{1}{m-1}\sum_{i=1}^{m}(b_i-\mu)^2} \tag{5}$$

After standardization $X=\{\mathrm{x_1,x_2,...,x_m}\}$, $X\subset R^{n\times m}$.

(2) Calculate the covariance of the standardized data set:

$$Cov=\frac{1}{m-1}\sum_{i=1}^{m}x_i^T x_i=\frac{1}{m-1}X^T X=(\mathrm{cov}_{ij})_{n\times n} \tag{6}$$

(3) Calculate the eigenvalues and eigenvectors of the covariance matrix: The covariance matrix has positive semi-definiteness, so there are similar diagonal matrices, and the problem is to solve the transformation matrix problem: $\lambda_i u_i=Cu_i$ [157]. Where, $\lambda_i(i=1,2,...,n)$ is the eigenvalue of the covariance matrix, u_i is the corresponding feature vector. Sort feature vectors in descending order: $\lambda_1>\lambda_2>...>\lambda_l$, $l\le \mathrm{n}$, Orthogonalize to get the feature vector: $\alpha_1,\alpha_2,...,\alpha_l$.

(4) Calculating contribution rate: the importance of a feature can be determined by the size of each feature value, and the cumulative contribution rate of the previous feature can be expressed as:

$$\theta=\frac{\sum_{i=1}^{k}\lambda_i}{\sum_{j=1}^{l}\lambda_j} \tag{7}$$

(5) Construct a new principal component feature: $Y=X\alpha$

The feature vector $Y=\{y_1,...y_m\}$, $Y \subset R^{m\times k}$ can be used as the feature after dimensionality reduction.

Through the above steps, the feature dimension is reduced from R^n to R^k. The advantage of the principal component analysis method is that the order of selecting principal components can be determined by the cumulative contribution rate, which reduces the computational workload. However, the meaning of the principal component is not as clear and explicit as the original variable, and the interpretability is poor. At the same time, it will also cause the lack of useful information due to the different choices of the cumulative contribution rate.

In summary, the above two methods both have shortcomings, and new methods are needed to improve and improve. This paper proposes a reduction method based on the minimization of the intra-class distance.

The sequence backward selection method can eliminate a feature through the function function, and then proceed in sequence, gradually narrowing the scope, to achieve the purpose of feature reduction, but for different objects and use conditions, different minimum functions need to be constructed. This kind of function construction is sometimes It is very difficult; at the same time, feature reduction is reduced item by item. When there are more features, the amount of calculation is larger, which is not conducive to online detection from time to time. In response to these shortcomings, combined with the characteristics of industrial robots and actual use conditions, a method of minimum distance within a category is proposed. The basic idea is to select the minimum average value of the distance within the category of the same fault feature under the premise of eliminating the influence of dimensions For the clustering effect of similar features, extract the feature with the smallest mean distance within the class, and then repeat the above steps to extract the features from the remaining features, and proceed in this way. Finally, three features with the smallest mean distance within the class are selected in turn to form the feature vector. Between faults, the feature vector is used to increase the degree of distinction between classes, and the remaining features are reduced, rather than item by item, which improves the efficiency of reduction and reduces the amount of calculation. The calculation formula of the minimum characteristic function is as follows:

$$\varphi_i = \frac{\sum_{j=1}^{n}\left(a_{ij}-\overline{x}_i\right)^2}{n\overline{x}_i^{\,2}} \qquad (1 \le j \le n) \tag{8}$$

$$\varphi_{\min} = \arg\min \varphi_i \qquad (1 \le i \le m) \tag{9}$$

Among them: n represents the number of samples, m represents the number of features, $\overline{x}_i$ represents the mean value of the i feature, a_{ij} represents the i value of the j feature, φ_i represents the relative distance objective function of the i feature, and $\varphi_{\min}$ represents i The objective function with the smallest relative distance among the features. Combine equations (8) and (9) together, that is, the minimum characteristic function.

Remove one feature each time, and multiply the remaining feature φ_i, as shown in equation (10):

$$F(V_k) = \arg\min \prod_{i=1}^{k} \frac{\sum_{j=1}^{n}\left(a_{ij}-\overline{x}_i\right)^2}{n\overline{x}_i^{\,2}} \qquad (1 \le j \le n, 1 \le i \le m, k=m-1) \tag{10}$$

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Constructing on the basis of formula (8), formula (10) is obtained, and formula (10) is the minimum function formula of the sequential backward selection method applied to the feature reduction of industrial robots; when using formulas (8) and (9) Calculate and sort. The selected parameters are optimized from small to large. The reduction effect is the same as the sequence backward selection method, which solves the problem of minimum function construction, but at the same time reduces the amount of calculation. Later, we will compare the effects of the above reduction methods through data and experimental analysis.

3. Comparison of experimental results

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The sequence backward selection method can eliminate a feature through the function function, and then proceed in sequence, gradually narrowing the scope, to achieve the purpose of feature reduction, but for different objects and use conditions, different minimum functions need to be constructed. This kind of function construction is sometimes It is very difficult; at the same time, the characteristics of a set of industrial robot bus current time-domain characteristic parameters tested by the experimental platform are shown in Table 1. The industrial robot actuator used in the experiment uses fixed-length signal collection. The collection length is 2000 points per group, and a total of 35 sets of data are collected. While collecting signals, 6 common time-domain statistical features are extracted: mean, standard deviation, Crest factor, kurtosis factor, slope factor and power factor. Apply the sequence backward selection method to the data in Table 3.1 to reduce the characteristic parameters, calculate according to formula (8), and the results are shown in Table 2:

Table 1 Experimental data table of industrial robot actuator signal

No.	Mean Standard	Deviation	Slope Factor	Kurtosis Factor	Crest Factor	Power Factor
1	3.66E-02	1.89E-04	-4.30E-09	2.04E-09	1.53E-02	1.34E-03
2	3.66E-02	1.88E-04	2.52E-08	2.05E-09	1.66E-02	1.34E-03
3	3.66E-02	1.83E-04	2.15E-09	1.80E-09	1.60E-02	1.34E-03
4	3.66E-02	1.92E-04	-8.05E-09	2.11E-09	1.49E-02	1.34E-03
5	3.67E-02	1.85E-04	1.19E-08	1.91E-09	1.60E-02	1.34E-03
6	3.67E-02	1.98E-04	-1.73E-08	2.75E-09	1.88E-02	1.35E-03
7	3.67E-02	1.88E-04	1.76E-08	1.96E-09	1.64E-02	1.35E-03
8	3.67E-02	1.76E-04	4.63E-09	1.61E-09	1.44E-02	1.34E-03
9	3.66E-02	1.75E-04	-1.59E-08	1.72E-09	1.60E-02	1.34E-03
10	3.66E-02	1.94E-04	5.69E-09	2.17E-09	1.58E-02	1.34E-03
11	3.66E-02	1.99E-04	5.30E-09	2.51E-09	1.63E-02	1.34E-03
12	3.66E-02	1.90E-04	1.86E-08	2.15E-09	1.64E-02	1.34E-03
13	3.66E-02	1.78E-04	8.69E-09	1.60E-09	1.41E-02	1.34E-03
14	3.66E-02	1.77E-04	4.85E-09	1.64E-09	1.52E-02	1.34E-03
15	3.67E-02	1.70E-04	-7.22E-09	1.33E-09	1.48E-02	1.34E-03
16	3.67E-02	1.87E-04	-6.79E-09	1.89E-09	1.46E-02	1.34E-03
17	3.67E-02	1.93E-04	1.85E-08	2.29E-09	1.74E-02	1.35E-03

18	3.67E-02	1.81E-04	1.82E-09	1.86E-09	1.59E-02	1.35E-03
19	3.67E-02	2.03E-04	-2.28E-08	2.66E-09	1.65E-02	1.35E-03
20	3.67E-02	1.97E-04	2.01E-08	2.40E-09	1.66E-02	1.34E-03
21	3.67E-02	1.77E-04	-2.21E-09	1.51E-09	1.55E-02	1.34E-03
22	3.66E-02	1.87E-04	-4.88E-09	1.97E-09	1.76E-02	1.34E-03
23	3.66E-02	1.84E-04	-4.33E-09	1.94E-09	1.73E-02	1.34E-03
24	3.66E-02	1.98E-04	2.44E-08	2.88E-09	1.81E-02	1.34E-03
25	3.67E-02	1.79E-04	1.98E-09	1.56E-09	1.34E-02	1.34E-03
26	3.66E-02	1.90E-04	2.10E-08	2.96E-09	1.98E-02	1.34E-03
27	3.67E-02	1.79E-04	1.20E-08	1.58E-09	1.47E-02	1.35E-03
28	3.67E-02	1.89E-04	2.28E-08	2.30E-09	1.70E-02	1.35E-03
29	3.67E-02	1.76E-04	2.24E-09	1.44E-09	1.38E-02	1.35E-03
30	3.67E-02	1.80E-04	6.29E-09	1.80E-09	1.68E-02	1.35E-03
31	3.67E-02	1.74E-04	8.29E-09	1.60E-09	1.58E-02	1.35E-03
32	3.67E-02	1.75E-04	7.55E-09	1.53E-09	1.59E-02	1.34E-03
33	3.67E-02	1.93E-04	-3.11E-09	2.54E-09	1.91E-02	1.34E-03
34	3.66E-02	1.74E-04	1.98E-08	1.52E-09	1.41E-02	1.34E-03
35	3.67E-02	1.82E-04	-8.65E-09	1.83E-09	1.61E-02	1.35E-03

Note: "E" is the symbol of scientific notation.

Table 2 The calculation results of the minimum characteristic function formula

name	Mean Standard	Deviation	Slope Factor	Kurtosis Factor	Crest Factor	Power Factor
symbol	φ_1	φ_2	φ_3	φ_4	φ_5	φ_6
the goal Function value	8.51×10^{-7}	1.94×10^{-3}	$1.49\times10^{+1}$	4.42×10^{-2}	8.58×10^{-3}	3.40×10^{-6}

Sort the parameters from largest to smallest $\varphi_3 > \varphi_4 > \varphi_5 > \varphi_2 > \varphi_6 > \varphi_1$。

According to the calculation of formula (10), the sequence backward selection method is used to perform feature reduction, and the process diagram of reducing to the remaining 1 parameter is shown in Figure 2:

$$\boxed{\varphi_1\varphi_2\varphi_3\varphi_4\varphi_5\varphi_6} \rightarrow \boxed{\varphi_1\varphi_2\varphi_4\varphi_5\varphi_6} \rightarrow \boxed{\varphi_1\varphi_2\varphi_5\varphi_6} \rightarrow \boxed{\varphi_1\varphi_2\varphi_6} \rightarrow \boxed{\varphi_1\varphi_6} \rightarrow \boxed{\varphi_1}$$

Figure 2 The feature reduction process diagram of the sequence backward selection method

In order to facilitate the comparison of the results, it was finally reduced to 3 features, using the sequence backward selection method to obtain 3 statistical features: mean, standard deviation, and power factor; using the within-class distance method for feature reduction, the 3 statistics obtained The characteristics are the same as the sequence backward selection method. In order to compare the two reduction methods more intuitively, Table 3 compares the number of runs of the two methods reduced to three statistical characteristics:

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Table 3 Comparison table of sequence backward selection method and within-class distance method

Name	Reduction result	Number of calculations	Number of comparisons	Total number of calculations
Sequence backward selection	same	15	15	30
Minimum distance within class	same	6	15	21

Through the application of the above examples, the reduction effect and the number of comparisons of the within-class distance method are the same as the sequence backward selection method, but the number of calculations should be significantly reduced, which can effectively improve the calculation speed. This method is beneficial to the computer to perform time-to-time calculations. . Especially when there are many parameters to be reduced, the calculation speed of the intra-class distance method will have obvious advantages.

The spatial clustering effect is compared based on the within-class distance minimum method and the principal component analysis method. Figure 3 is the feature space generated by the three features obtained by the method of minimizing the distance within the class. The principal component analysis method is used for feature reduction, and the principal component contribution rate is 80%, and the first three-order principal component contribution rate is 88.24%. The clustering effect diagram is shown in Figure 4.

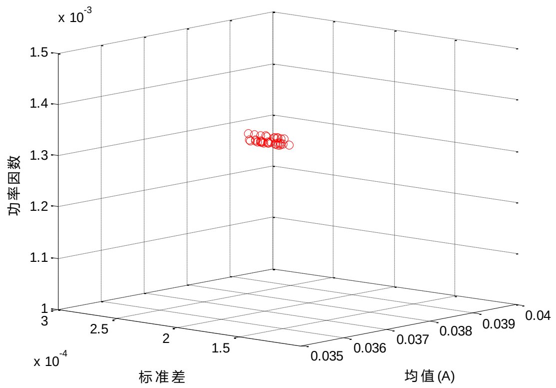

Figure 3 The clustering effect diagram generated by the feature reduction method of the within-class distance minimum method

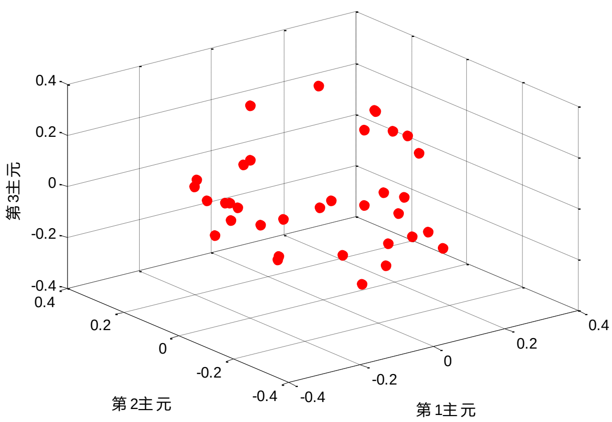

Figure 4 The clustering effect diagram generated by the principal component analysis method of three-order principal components

Through the comparison and analysis of Fig. 3 and Fig. 4, three principal elements are also retained. The clustering effect of the minimum intra-class distance method is relatively ideal, while the clustering effect of the PCA method is poor.

4. Conclusion

This paper proposes a model for feature reduction of industrial robots, and conducts in-depth research on the model. It is analyzed through experiments and compared with the typical feature reduction method, which proves that this method has faster calculation speed and better clustering effect. This method effectively improves the correct rate of fault diagnosis, and is suitable for online and real-time fault diagnosis. The method proposed in this paper not only requires less calculation than the sequence backward selection method, and has a better clustering effect than the principal component analysis method. It can also be directly used for the fault classification of industrial robots, which also reflects the advantages of the method proposed in this paper. Advantage. This method provides references and references for other equipment status diagnosis and prediction, and becomes one of the powerful tools for status diagnosis and prediction. At the same time, the feature reduction model proposed in this paper is a further improvement and development of the existing feature reduction model.

In summary, this paper studies the feature reduction model of industrial robot actuators, and proposes a new feature reduction model. Due to the limitations of time, experimental conditions and energy, the model still needs to be further improved: First, when there are too many parameters for feature reduction, the model requires a large amount of calculation, and the algorithm needs to be further optimized; second, When the parameter similarity of feature reduction is too high, the effect of clustering is not ideal, which requires improvement of the model and further perfection in theory.

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