OPTIMUM CHOICE OF SIGNALS' FEATURES USED IN TOOTHED GEARS' DIAGNOSIS

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Summary

The article proposes an algorithm to choose optimum diagnostic features used in toothed gears' diagnosis. The test object is a single-bevel gear in the research area. From the gear in two technical states there were collected vibration signals and eight features were calculated. Feature and machine state correlation degree depends on the type of damage and analyzed object properties. Some features are insensitive to particular damage or may transmit the same information. Signal features choice is a crucial step which influences the final technical condition evaluation. With the algorithm that automatically verifies features' usability there were chosen four best correlated with the technical condition of the object. Gear state classifiers were two neural networks, one formed of four features and the other of all eight. The other one was set to check features' choice accuracy.

Keywords: bevel gear, feature selection, artificial neural network.

OPTYMALNY WYBÓR CECH SYGNAŁÓW WYKORZYSTYWANYCH
W DIAGNOZOWANIU PRZEKŁADNI ZĘBATYCH

Streszczenie

W artykule przedstawiono algorytm doboru optymalnych cech diagnostycznych używanych w diagnozowaniu przekładni zębatych. Obiektem badań była przekładnia jednostopniowa stożkowa badana na stanowisku badawczym. Z przekładni w dwóch stanach technicznych zarejestrowano sygnały drgań i obliczono osiem cech. Stopień korelacji cechy ze stanem maszyny zależy od rodzaju uszkodzenia i właściwości analizowanego obiektu. Niektóre cechy nie są czułe na dane uszkodzenie, lub mogą przekazywać tę samą informację. Wybór cech sygnału jest krytycznym krokiem, który ma wpływ na ostateczny wynik oceny stanu technicznego Za pomocą algorytmu, który w sposób automatyczny weryfikuje przydatność cech wybrano cztery najbardziej skorelowane ze stanem technicznym obiektu. Klasyfikatorem stanu przekładni były dwie sieci neuronowe, pierwsza utworzona dla czterech cech a druga dla wszystkich ośmiu. Druga sieć miała na celu sprawdzenie poprawności wyboru cech.

Słowa kluczowe: przekładnia stożkowa, selekcja cech, sztuczne sieci neuronowe.

1. INTRODUCTION

Technical condition deduction especially in an early stadium of damage development and noisy vibroacoustic signals needs signal processing. There are many methods used successfully. Among them there are statistical methods, time and frequency analyses such as Wigner-Ville distribution and short time Fourier transformation, wavelet analysis, bispectrum analysis, cepstrum. Statistical methods are quite easy but effective method in machines' technical condition evaluation. Many researchers confirmed its effectiveness in toothed gears' diagnosis [4, 8]. Most frequently used are time features such as RMS, kurtosis, crest factor, frequency features and features specially created for toothed gears testing FM0, NA4, NB4 [6]. Numerous features (mentioned in literature there are more than twenty [3, 10]) cause the diagnosing person problems with tracing them and their interpretation, especially when features' trends are inconsistent. Feature and machine state correlation degree depends on the type of damage and analyzed object properties. Some features are insensitive to particular damage or may transmit the same information. Signal features choice is a crucial step which influences the final technical condition evaluation [9].

Features selection may be done automatically. Using different methods it is possible to get optimal data fast and objectively. Combining statistical methods with artificial intelligence we get a credible and efficient tool to detect tooth gears' damages. In [1] using the time and frequency features there was multi-bevel gears' state diagnosed – the gears are used in transportation in coal mine. Using the main

PCA components analyze big redundancy of data was confirmed and their size was reduced what built up their usability in further technical condition analyze. Yang [9] used time and frequency measures which were used as an input data for the neural network to evaluate the reliability of induction motor. Reduction of the data size from thirteen to three was obtained by using the features' extraction method [10]. Similar algorithm was used by Lei [3] to choose more features sensitive to damages in electric motor bearings. Artificial neural networks and SVM (Support Vector Machine) method were used do detect pitting by Samanta [5]. As an input vibration signal features optimized with genetic algorithms were used. In the problem of class differentiation, where genetic algorithms were classifiers, Zhu [11] used RIF (Relative Importance Factor) method to detect less important to classification process features. Removal of these improved class identification.

To evaluate technical condition of the toothed gear signal features which were the input data for the neural network there were used in this work. There were used time and frequency features together with specially designed for gears' diagnosis FM0, NB4, frequently mentioned in NASA technical reports [2]. Neural network classified the gear state as „good" or „bad". Large number of features on input implicates longer teaching and calculation time and bigger number of cases. In addition to this, if the data is not linked to the technical condition, state classification error may rise. In consequence, to choose only highly correlated with the gear technical condition features the algorithm described in [3, 9] was used.

2. VIBRATIONS MEASUREMENT AND THE TEST OBJECT

Test station was formed with two toothed gears, electric motor, water brake and control measurement instruments. Electric motor rotary speed was set using the control unit which enables research with different rotary speed. Additionally, the rotary speed was raised using cylindrical wheel multiplier mounted between the motor and the tested gear. Brake load was changed in several ranges. Moment transferred by shafts and clutches. The test object was a single-bevel gear. The driving wheel had 19 teeth, and driven 42 teeth. Both input and output shafts were propped by two rolling bearings.

Kinematical scheme of the gear is shown in Fig. 1. The test object was New. In the test two pairs of toothed wheels were tested, first pair had side teeth surfaces damaged after trowelling, second pair was undamaged.

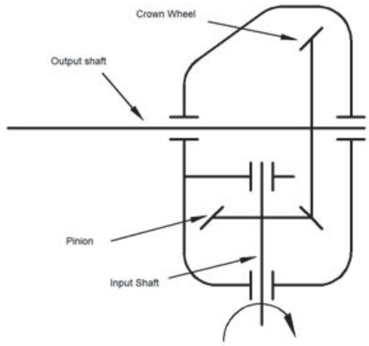

Fig. 1. Kinematical scheme of the tested gear

The measurement system was forded from a controller, National Instruments measurement cards and two triaxal Bruel&Kjaer sensors. Sensors location on the gear is show in Fig. 2. Sampling frequency was 40 kHz. Presented figures are for the maximum rotary speed of the input shaft equal 6196 rpm and load equal 34 % maximum load.

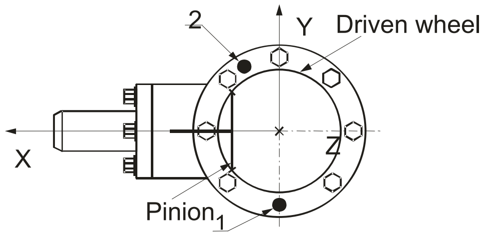

Fig. 2. Sensors 1 and 2 location on the gear

3. FEATURES SELECTION ALGORITM

Eight features were calculated for presented signals – three in time domain and five specially created for gears' diagnosis. Formulas for three first features (kurtosis k, crest factor C and impulse factor I) may be found in literature [2] and the other measures in [2, 4, and 6].

Since many measures lengthens calculation time and may cause limitations to neural network's ability to generalize algorithm presented in [3, 10] was used to choose optimum features. The input data is three-dimensional array M_c x C x J, where: J is a number of signal features, M_c number of values for each of the features and C number of object states. $p_{m,c,j}$ is read as m value of j measure for c state of the object, where: $m=1,2,\dots,M_c$; $c=1,2,\dots,C$; $j=1,2,\dots,J$. In this work two states of the object are concerned ($C=2$) for which eight features were calculated ($J=8$) with two hundred twenty-nine values (M_c = 229). Calculation method consists of following steps

[3, 9]:

Step (1)

Calculate average distance between particular values of measures in the same state

$$D_{c,j} = \sqrt{\frac{1}{M_c \times (M_c - 1)} \sum_{l,m=1}^{M_c} (p_{m,c,j} - p_{l,c,j})^2}\ , l,m = 1, 2, \dots, M_c$$

Next, calculate average distance for C states of the object

$$D_j^{(w)} = \frac{1}{C}\sum_{c=1}^{C} D_{c,j}$$

Step (2)

Calculate $V_j^{(w)}$ according to the formula:

$$V_j^{(w)} = \frac{\max(D_{c,j})}{\min(D_{c,j})}$$

Step (3)

Calculate average distance for all values of measures for the same state

$$a_{c,j} = \frac{1}{M_c}\sum_{m=1}^{M_c} p_{m,c,j}$$

Next, get the average distance between the values for different states

$$D_j^{(b)} = \sqrt{\frac{1}{C\times(C-1)}\sum_{c,e=1}^{C}(a_{e,j}-a_{c,j})^2}, c,e = 1,2,\ldots,C$$

Step (4)

Calculate $V_j^{(b)}$ for the object in a different state

$$V_j^{(b)} = \frac{\max(|a_{e,j}-a_{c,j}|)}{\min(|a_{e,j}-a_{c,j}|)}, c,e = 1,2,\ldots,C$$

Step (5)

Calculate λ_j as below:

$$\lambda_j = \left(\frac{V_j^{(w)}}{\max(V_j^{(w)})} + \frac{V_j^{(b)}}{\max(V_j^{(b)})}\right)^{-1}$$

Step (6)

Calculate the $D_j^{(b)}$ and $D_j^{(w)}$ ratio and E_j

$$E_j = \lambda_j \frac{D_j^{(b)}}{D_j^{(w)}}$$

Next normalize E_j by maximum value and get the evaluation criteria

$$\overline{E}_j = \frac{E_j}{\max(E_j)}$$

Dividing E_j by the maximum value causes the figures range 0 to 1. The closer to 1, the better this feature reflects the object state. Choice can be made using the criteria $\overline{E}_j \geq P$, where P is a chosen threshold value for the features.

4. METHOD AND RESEARCH RESULTS

4.1. Features choice

Figure 3 shows results of features' sensitivity evaluation according to the algorithm described above. Assuming threshold equals 0.5 four features were chosen: kurtosis, crest factor, impulse facto rand NB4.

To verify features choice neural networks were built for four chosen measures and all eight measures.

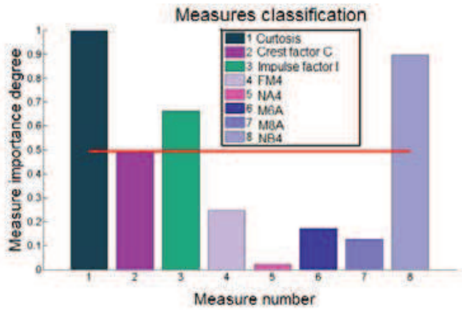

Fig. 3. Measures' sensitivity to damage evaluation

4.2. Neural networks

To create neural networks Statistica packet was used. Optimal networks were sought by Automatic Network Seek. Two types of networks were taken into consideration MLP and RBF. Different variants of networks: formed by different neuron numbers in the hidden layer, five hidden neuron activation and output functions (linear, logistic, tanh, expotential, and sinus). Best results for four features were received for MLP network with one hidden layer with nine neurons. Hidden neuron activation function was linear and output softmax. For eight features optima network is a MLP network with one hidden layer with four neurons, linear activation function and output logistic.

In version 8 of Statistica quality criteria implicates neural usability. Quality is calculated for teaching data, testing data and if there is such a set validation data. For classification problem quality is a relative number of cases successfully classified (referred to the total number of cases) presented in percentage terms [8].

5. RESULTS ANALYZE

Neural network was used to assign the gear state to one of two classes. In table 1 there are results for the data from the sensor 1, which was used in teaching process, testing and network validation. Testing data is used in the teaching process until the teaching is finished so that the network does not lose the ability to generalize when over taught. To check network's accuracy frequently third set of validation data is used - not used before in the teaching process so the validation quality is used to evaluate neural network. In case of the network formed for four features validation quality was 98.5 % and for eight variables on the input 89.7 %. Limiting features number by half caused nearly 9 % rise in gear state classification accuracy.

Table 1. Research results for data from sensor 1

No.	Number of features	Network type	Teaching quality [%]	Testing quality [%]	Validation quality [%]
1	4	MLP 4-9-2	96,27	97,06	98,53
2	8	MLP 8-4-2	81,99	94,12	89,70

Networks were checked also for the data from the other vibration sensor. In the network implementation mode after the addition of output variable there is only available quality testing (different meaning than when network teaching). For networks with four variables on the input testing quality was 100 %, when for eight variables 44.3 % (table 2).

Table 2. Research results for data from sensor 2

No.	Number of features	Network type	Testing quality [%]
1	4	MLP 4-9-2	100,00
2	8	MLP 8-4-2	44,32

6. SUMMARY

Using statistical methods in machines' diagnosis problem of too many signal features may arise. It may cause limited accuracy in state evaluation and lengthen the calculation time. Automatic choice of adequate features accelerates the process of creating a diagnostic system and for a researcher with little experience is a great help.

One of the basic applications of neural networks is classification. Crucial stage deciding on the correct network operation is relevant data choice (variables) reflecting appropriate classes. Frequently the quantity of data is not too big and the more variables are used in the teaching process the more cases are needed.

To detect the toothed wheel damages statistical methods were used in connection with neural networks. To improve the evaluation accuracy only features well correlated with the device chosen by the features' selection algorithm were used. Limiting the number of features from eight to four improved the classification accuracy by almost 9% to equal 98.5%. However, in both cases the results were satisfying. In contrast to this were the results for the data from sensor 2. The neural network in implementation mode for four features 100 % distinguished the gears' states when for eight features quality was 44, 3 % which is not a satisfying result.

7. LITERATURE

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