Modeling of Laser Cladding High Entropy Alloys Friction and Wear Monitoring

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Abstract: Aiming at the problem of low precision of traditional wear monitoring model, a friction and wear monitoring model of laser cladding high entropy alloys is constructed. After decomposition of the input wear signal by wavelet packet decomposition, FFT is used to extract the characteristic parameters in the decomposition sequence. Taking the characteristic parameters as the parameters of the neural network, the training sample set is used to train the neural network. Wear data were analyzed by using neural network after training. Combining d-s theory to determine the relevant parameters of the model and improve the monitoring accuracy, the construction of the monitoring model is completed. Compared with the traditional monitoring model, the monitoring precision of the established monitoring model is about 3 times that of the traditional monitoring model, which is more suitable for monitoring the friction and wear of laser cladding high entropy alloys.

Keywords: Laser cladding; High entropy alloys; Friction wear; Monitoring and modeling

1. Introduction

In terms of the development of human ability to develop materials, the alloys composition has gone through a process from simple to complex. The continuous improvement of the function and performance of the alloys promotes the progress of human civilization. As a new hotspot in the field of alloys, high entropy alloys are widely concerned and studied because of their excellent properties. High entropy alloys with excellent properties can be obtained by selecting appropriate components and compositions. High entropy alloys with multiple components can effectively improve the microstructure and properties of alloys. Compared with traditional alloys, high entropy alloys have excellent properties such as high strength and hardness, excellent corrosion resistance and thermal stability, good fatigue resistance and fracture strength. In the high entropy alloys using laser cladding coating material of substrate surface is selected by the laser irradiation make a thin layer of melted at the same time, the sum of the substrate and forming a low dilution degrees after rapid solidification, and matrix combination of metallurgical bonding surface coating, at the same time of improving the wearability high entropy alloys and save a lot of valuable elements. In combination with the characteristics of high entropy alloys themself, laser cladding further improves the surface properties of the alloys and widens the application range of high entropy alloys [1].

In order to monitor the friction and wear degree of laser cladding high entropy alloys the traditional monitoring model usually only monitors the integrity of the cladding coating of high entropy alloys. Monitoring of high entropy alloys is usually divided into indirect and direct monitoring [2]. Direct monitoring is to monitor the friction and wear of alloys through tools. Indirect monitoring is through the sensor contact monitoring or through infrared, laser and other means of detection. However, the traditional monitoring has the problem of low monitoring accuracy, so this paper will establish a model to monitor the friction and wear of laser cladding high entropy alloys.

2. Laser Cladding High Entropy Alloys Friction and Wear Monitoring Model

The overall block diagram of the friction and wear detection model of laser cladding high entropy alloys is shown in figure 1. The high entropy alloy wear changes detected by the laser sensor are input into the detection model in the form of signals. The detection model processes the signal by wavelet packet decomposition and extracts the characteristic parameters from the decomposition results by FFT. Taking the characteristic parameters as the parameters of the input layer of the neural network, the wear data are analyzed by training and testing the neural network. Combined with d-s theory, the monitoring model is built by setting up relevant parameters and improving the monitoring accuracy.

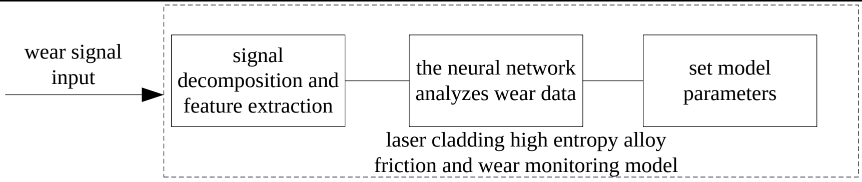

Figure 1. Overall block diagram of laser cladding high entropy alloys friction and wear monitoring model

2.1. Wear signal decomposition and feature extraction

The wear signal of high entropy alloys transmitted by laser sensor needs to be processed by wavelet packet decomposition. Wavelet packet decomposition is a band decomposition technique, which is extended from wavelet analysis and a method for more detailed analysis and reconstruction of signals [3]. The signal transmitted by the sensor is decomposed into 8 independent frequency bands, and then the wavelet packet decomposition coefficients of 8 nodes are reconstructed to extract the wavelet packet values of 8 sub-bands. Wavelet transform has multiresolution and can decompose signal into simple branches carrying different frequency band information without losing energy, which is suitable for multi-scale analysis. For a finite energy function $f(t)$, which satisfies $f(t) \in L^2(R)$, its continuous wavelet transform is as follows:

$$W_f(a,b) \le f(t) \tag{1}$$

$$\psi_{a,b} \ge \int_{-\infty}^{+\infty} f(t)\psi_{a,b}^{*}(t)dt \tag{2}$$

Function system

$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$ $(a>0)$ is the scale factor; $b \in R$ is the translation factor; $\psi(t)$ is the female wavelet. $\psi_{a,b}(t)$ is a wavelet basis function generated by scaling and time translation of $\psi(t)$ [4]. Through the change of scale factor a and translation factor b, the wavelet window moves along the time axis, and the function on the whole time axis is analyzed on different scales. Figure 2 is a schematic diagram of three-layer wavelet packet decomposition.

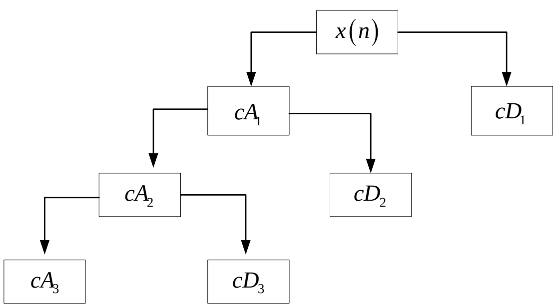

Figure 2. Schematic diagram of three-layer wavelet packet decomposition

From the point of view of signal filtering, wavelet packet decomposition is to filter the decomposed signal through a low-pass filter and a high-pass filter, respectively. After decomposition, a group of low-frequency signals and a group of high-frequency signals are obtained respectively, and the signal is further decomposed. The coefficients of cA_j and cD_j at different scales are obtained by wavelet decomposition using orthogonal wavelet basis. The frequency range of low-frequency component $A(k)$ and high-frequency component $D(k)$ obtained after each decomposition is as follows:

$$\begin{cases} D(k):\left[2^{-(j+1)}f_s, 2^{-j}f_s\right] \\ A(k):\left[0, 2^{-(j+1)}f_s\right] \end{cases} \tag{3}$$

In formula (3), j=1,2... M; f_s is the signal sampling frequency [5]. After wavelet packet decomposition of the wear signal, FFT is used to extract the wear characteristics from the decomposed information sequence. The singular value is used as the characteristic parameter to describe the friction and wear process.

According to the definition of singular value decomposition, let's say that A is an m×n matrix, there must be an orthogonal matrix, such that A= USVT, where S is a diagonal matrix. $S = \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix}$, $\Sigma = diag(\lambda_1, \lambda_2, \cdots, \lambda_r)$, r=rank（A）.The singular values of its diagonal elements, namely A, are arranged in descending order, namely $\lambda_1 \ge \lambda_2 \ge \cdots \ge \lambda_r$. If these non-zero singular values form an eigenvector $d = (\lambda_1, \lambda_2, \cdots, \lambda_r)$, it can be known from the properties of matrix singular values that the eigenvector can be used as an eigenparameter to uniquely represent the matrix [6]. The extracted characteristic parameters need to be normalized according to formula (4). Take the maximum value $x_{\max}$ and the minimum value $x_{\min}$ of the parameters, and make the characteristic parameters in the same quantity level through the following processing.

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{4}$$

After the characteristic parameters are normalized, the friction and wear data of laser cladding high entropy alloys are analyzed by using neural network.

2.2. Wear data analysis

After the normalization of the characteristic parameters, the tri-layer feed forward neural network was used to analyze the friction and wear data of laser cladding high entropy alloys. In the neural network structure shown in figure 3, there are n nodes in the input layer, p nodes in the hidden layer, and q nodes in the output layer. Q output nodes correspond to the friction and wear state of q high-entropy alloys, respectively. The input value of input layer is the characteristic parameter after normalization treatment, and the activation function of hidden layer and output layer is sigmoid function. Training samples are needed to train the neural network. After the training neural network meets the error requirements, the wear data can be analyzed by inputting test samples [7].

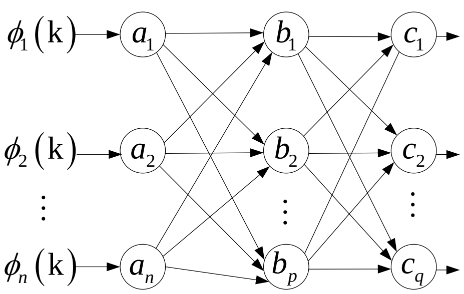

Figure 3. Three-layer feed forward neural network structure

Input the training sample data into the input layer of the neural network, and process the input sample data according to the characteristic parameters in the input layer. Input the processing results into the hidden layer and the output layer, and output the trained data set after activation by the activation function sigmoid. Error test is carried out on the data set after output. After the error test, if the error accuracy is 0.001, the training is completed. If the error accuracy does not meet 0.001, reset the initial parameters of the activation function and train again until the error meets the accuracy. After the training, the neural network needs to be tested with the test sample set. When the output value of the ith node in the output layer of neural network is greater than 0.99, and the output value of other nodes is less than 0.01, the wear state of this analysis is considered as the ith [8]. After the analysis of friction and wear data, in order to avoid errors caused by single monitoring by neural network, D-S theory was used for decision-making level monitoring, wear monitoring model parameters were set, and the friction and wear monitoring model of laser cladding high-entropy alloys was established.

2.3. Establish wear monitoring model

After the training of the neural network, the parameters of each layer of the neural network are determined. After the test of the sample set, the output of the neural network meets the precision of monitoring the wear of laser cladding high entropy alloys. In order to prevent errors caused by single neural network monitoring and improve monitoring accuracy, D-S theory is adopted to set model parameters.

When function m: $2^U \to [0,1]$ satisfies the $\sum_{A\subset U} m(A)=1$ and $m(\phi)=0$ conditions, m (A) is the basic probability assignment of A, indicating the precise trust degree of A. The trust function and truth-like function of A can be expressed as formula (5) and formula (6), bel (A) represents the sum of probability measures of all subsets of A, pl (A) represents the trust degree that does not deny A. If m (A) >0, A is called the focal element of trust function bel. Let m A_1 and m A_2 be the basic probabilities of unequal maximums and minimums in the wear errors. If,

$$bel(A)=\sum_{B\subset U} m(B) \tag{5}$$

$$pl(A)=1-bel(A) \tag{6}$$

So bel (A) is the judgment result, $\sum_{B\subset U} m(B)$ is the pre-set threshold [9]. Taking the training error of neural network as an uncertain factor, the calculation formula is as follows:

$$\begin{cases} m(A_1)-m(A_2)>\varepsilon_1 \\ m(U)<\varepsilon_2 \\ m(A_1)>m(U) \end{cases} \tag{7}$$

Then the basic probability assignment of each focal element is:

$$m(A_i)=\frac{y(A_i)}{\sum_{i=1}^{n} y(A_i)+e_r} \tag{8}$$

In formula (8), $y(A_i)$ is the output of each node of the neural network, and n is the number of output nodes of the neural network. After the basic probability assignment is obtained, the probability assignment of different wear amounts is fused to improve the monitoring accuracy [10]. After setting the relevant parameters of the wear monitoring model according to the d-s theory, test the whole monitoring model with test samples again. When the output result of the model is better than the monitoring error value originally set, it is concluded that the model can monitor the wear of laser cladding high entropy alloys. Thus, the establishment of friction and wear monitoring model of laser cladding high entropy alloys is completed.

3. Model Performance Test Experiment

A piece of high entropy alloys cut by laser cladding is divided into two parts, and then two parts of high entropy alloys are divided into the same number of alloys blocks as the experimental object. The laser cladding high entropy alloys of the same size were tribally treated by two friction and wear testing machines. The wear information of high entropy alloys was collected by laser sensor, and the friction and wear of high entropy alloys were monitored by the monitoring model constructed in this paper and the traditional monitoring model respectively. Taking the traditional monitoring model as the control group and the monitoring model constructed in this paper as the experimental group, the accuracy of the two monitoring models in monitoring the wear of high-entropy alloys was verified by recording the monitoring data of the two monitoring models on the wear of high-entropy alloys.

3.1. Experimental environment and procedures

The experimental environment is shown in figure 4. The wear test was completed on the SFT-2M pin - disc friction and wear test machine. The parameters of the friction and wear testing machine were set as follows: speed of 500 r/min, load of 50 N, wear time of 20 min, wear linear velocity of 9.42m/min. The laser cladding high entropy alloy was fixed on the friction and wear test machine, and the laser sensor was placed in an appropriate position to monitor the wear of the alloy block.

The wear amount of high entropy alloys is controlled by computer friction and wear testing machine. A laser sensor was installed to monitor the friction wear of two high entropy alloys during the experiment. Under the condition that other experimental conditions remain unchanged, the two monitoring models simultaneously monitor the input wear quantity data and output the monitoring results.

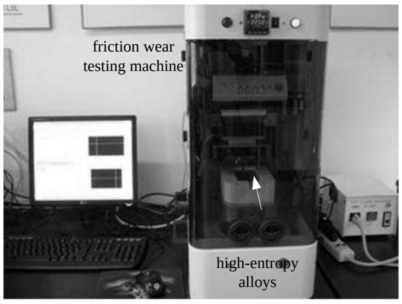

Figure 4. Experimental environment

3.2. Experimental results

The experimental results ignore the small errors caused by the differences between the two friction and wear testing machines, and remove the experimental results with large errors in the experimental data. The comparison results of 10 times of wear monitoring of laser cladding high-entropy alloys by the two monitoring models are shown in table 1.

Table 1. Comparison results of monitoring wear between the two models

Serial number	Actual wear /mm	Wear was monitored in the experimental group /mm	Control group monitoring wear /mm
1	0.18	0.17	0.26
2	0.20	0.25	0.29
3	0.26	0.24	0.36
4	0.28	0.27	0.34
5	0.24	0.24	0.27
6	0.25	0.21	0.29
7	0.22	0.18	0.36
8	0.18	0.23	0.34
9	0.29	0.27	0.33
10	0.16	0.19	0.36

It can be analyzed from the comparison results of monitoring wear of the two models in table 1, the absolute error between the experimental group data and the actual value is 0.027, and the absolute error between the control group data and the actual value is 0.094. The average relative error of monitoring laser cladding high entropy alloys is 0.095. According to the comparative analysis of the data of the experimental group and the control group in the table, the data of the experimental group is obviously smaller than that of the control group, and is closer to the actual wear. From the perspective of error results, the absolute error of the experimental group is much smaller than that of the control group, and from the perspective of error value, the absolute error of the experimental group is about one third of that of the control group, that is, the monitoring accuracy of the monitoring model constructed in this paper is about three times that of the traditional monitoring model. In conclusion, the accuracy of the friction and wear monitoring model of laser cladding high-entropy alloys constructed in this paper is higher than that of the traditional friction and wear monitoring model, which should be popularized.

4. Conclusion

In this paper, a monitoring model of laser cladding high entropy alloys friction and wear is established. The friction and wear data series of laser cladding noble alloys are processed by wavelet packet decomposition, and the wear characteristics are extracted by FFT. The extracted characteristic parameters are taken as the parameters of the input layer of the neural network, and sigmoid function is used to activate the hidden layer and output layer. After training the neural network with training sample set, the output error accuracy is verified. After the output precision meets the requirements, the test sample data is input to the neural network to complete the test of the neural network. D-S theory is used to improve the monitoring accuracy of the monitoring model, determine the monitoring model parameters, and complete the model construction. Through the comparison with the traditional monitoring model, the superiority of the monitoring model constructed in this paper is verified.

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