Research Article

Magnetic-Acoustic Feature Extraction and Damage Fusion Evaluation of 45 Steel Specimens during Fatigue Process for Remanufacturing

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To clarify the changes of the magnetic-acoustic features of 45 steel specimens during fatigue damage, an experimental platform was built to carry out magnetic memory and acoustic emission detection. The magnetic memory and acoustic emission signals of specimens in different damage states were collected, and the multi-scale entropy characteristics of magnetic memory signals, as well as the wavelet packet energy spectrum and singularity index characteristics of acoustic emission signals, were further extracted. A magnetic-acoustic feature fusion and damage assessment model was constructed by using Naive Bayes method. Results show that the average value of multi-scale entropy of normal magnetic field intensity increases gradually with the increase of fatigue cycles, and the average value of multi-scale entropy of magnetic field intensity gradient gradually decreases. The cumulative ringing count and energy spectrum (proportion of frequency band 1) of acoustic emission signals decrease with the increase of fatigue cycles, while the amplitude singularity index gradually increases. The established model has high evaluation accuracy, and the conclusions of this paper can provide basic methods and data support for fatigue damage evaluation of remanufactured components.

1. Introduction

Remanufacturing is a new type of manufacturing method derived from traditional manufacturing, which has been widely used to restore and improve the performance of high-value parts due to its energy-saving, material-saving, and environment-friendly features. Fatigue damage is a typical damage form of remanufactured components, and the effective detection of fatigue damage is an important measure to guarantee the smooth progress of remanufacturing engineering. Due to the complex service environment of ferromagnetic components, the damage detection results are greatly affected by the environment (such as noise and magnetic field), and it is difficult to quantify and accurately evaluate fatigue damage by a single nondestructive testing method. Since magnetic memory and acoustic emission characteristics are more sensitive to the early stress concentration of ferromagnetic components and can monitor the damage condition in real time, carrying out magnetic-acoustic feature fusion and damage assessment can make up for the deficiency of single feature detection and provide new ideas for the quantification of fatigue damage of remanufactured ferromagnetic components.

Under the action of cyclic load, small-damage incidents such as dislocations and cyclic slips are formed inside the material [1–3]. In the micro-damage region, the magnetic domain structure caused by the magnetomechanical effect is reoriented, and a leakage magnetic field is generated on the surface of the component. At the same time, the internal fatigue micro-damage of the material will cause the release of
energy to generate transient elastic waves that are transmitted to the material surface. The magnetic-acoustic characteristics of the fatigue process derive from the same damage source. In the investigation of the magnetic characteristics of the fatigue damage process, a magneto-mechanical model was established based on the analysis of the physical mechanism of the magnetic memory effect [4]. The correlation analysis of the magnetic memory signal with the degree of stress concentration was carried out [5], revealing the variation rule of magnetic memory signal under quasi-static and fatigue loads [6, 7] and describing the effects of different initial magnetic states, external magnetic field, and temperature on the magnetic signal [8, 9]. In addition, magnetic features are also used to predict fatigue crack propagation paths of remanufactured components [10]. By extracting magnetic features such as multidimensional signals [11], magnetic flux leakage parameters [12], and fuzzy entropy [13], the research on structural failure prediction [14], residual stress evaluation, fatigue life characterization, and cumulative plastic damage quantification of ferromagnetic components is carried out [15, 16]. In addition, acoustic emission technology has also been used for fatigue crack propagation prediction [19], fatigue damage identification, and damage monitoring [20, 21] of in-service components.

However, damage assessment of ferromagnetic components based on magneto-acoustic characteristics still faces challenges. For example, it is difficult to quantify damage by directly using normal magnetic field intensity $H_p(y)$, magnetic field intensity gradient $K$, acoustic emission ringing count, amplitude, and energy information obtained in the damage process. The existing single-scale magnetic signal fails to reflect the scale effect and complexity characteristics of the signals, and there is a data bottleneck in the damage quantification process, which also leads to the difficulty in establishing an accurate damage prediction model.

In this paper, 45 steel specimens were used as objects to carry out the study of the magnetic-acoustic feature extraction and damage assessment. The magnetic memory and acoustic emission signals of the fatigue damage process were collected, and the multi-scale entropy characteristics of the magnetic memory signals, as well as the wavelet packet energy spectrum and the singularity index characteristics of the acoustic emission signals, were extracted. The Naive Bayes method was applied to construct the magnetic-acoustic feature fusion and damage assessment model.

### 2. Methods

#### 2.1. Magnetic Memory Feature Extraction Method

When the ferromagnetic component materials are subjected to cyclic loading, micro-damage events such as dislocations, cyclic slip, and micro-crack will be formed inside them. The stress distribution in the region of micro-damage is inhomogeneous, and there exist multiple internal friction mechanisms (viscoelastic internal friction, dislocation internal friction, etc.) with high stress energy. To counteract the stress energy, the magnetic domains in this region are reoriented and aligned to form magnetic poles triggered by magneto-mechanical effect and generate leakage magnetic fields on the surface of components. The above-mentioned magnetic memory signals can be acquired by a magnetic memory detection device.

The magnetic memory signals include $H_p(y)$ and $K$. In order to extract magnetic memory features and describe the variation law of complexity for time series of magnetic memory signals at different scales, the multi-scale entropy method was adopted for magnetic memory feature extraction. The multi-scale entropy method derives from the sample entropy, which integrates the scale factor of time series, and the method is described as follows [22]:

1. Suppose the time series of $H_p(y)$ is \( \{x_1, \ldots, x_n\} \), $N$ is the length of sequence.

2. Construct a continuous coarse-grained time series \( \{y^{(r)}\} \):

   \[
   y^{(r)}(j) = \frac{1}{\tau} \sum_{i=(j-1)r+1}^{jr} x_i \quad (1 \leq j \leq \frac{N}{\tau}),
   \]

   \( \tau \) is the scale factor. When \( \tau = 1 \), the sequence \( \{y^{(r)}\} \) is the original time series. Generally, take $\tau_{\text{max}}=10$.

3. According to the change of the scale factor $\tau$, a time series of length $N=L/\tau$ is obtained, which constitutes a set of $m$-dimensional vectors $[Y^{(r)}(1), \ldots, Y^{(r)}(i), Y^{(r)}(N-m+1)]$ by successive serial numbers. Among them,

   \[
   Y^{(r)}(i) = [y^{(r)}(i), y^{(r)}(i+1), \ldots, y^{(r)}(i+m-1)]
   \]

   \((i = 1 \sim N - m + 1)\). These vectors represent $m$ consecutive $y$ values starting from the $i$-th point at scale $\tau$.

4. Define the distance between $Y^{(r)}(i)$ and $Y^{(r)}(j)$. d

   \[
   d[Y^{(r)}(i), Y^{(r)}(j)] = \max_{k} y^{(r)}(i+k) - y^{(r)}(j+k).
   \]

   Among them, the value range of $k$ is $0 \sim m-1$, the value range of $i$ and $j$ is $1 \sim N - m + 1$, and $i \neq j$.

   For each value of $i$, calculate the distance $d[Y^{(r)}(i), Y^{(r)}(j)]$ between $Y^{(r)}(i)$ and the rest of the vector $Y^{(r)}(j)$.

5. For a given threshold $r$, count the number of $d[Y^{(r)}(i), Y^{(r)}(j)]$ less than $r$ for each $i$ value and the ratio of this number to the total distance $N-m$, denoted as $C_{r,m} (r)$.
\[
C^r_m(r) = \frac{1}{N - m} \sum_{i,j=1}^{N-m} \delta \left[ Y^r(i), Y^r(j) < r \right]
\]
\[
(i, j = 1 \sim N - m + 1; i \neq j).
\]
where the probability \(C^r_m(r)\) is the degree of correlation between all \(Y^r(i)\) and \(Y^r(j)\), which indicates the degree of regularity of the signal time series \(\{Y^r(t)\}\).

(6) Find the average value of \(C^r_m(r)\) over all \(i\):
\[
C^r_m = \frac{1}{N - m + 1} \sum_{i=1}^{N-m+1} C^r_m(r).
\]

(7) Increase the number of dimensions to \(m+1\) and repeat steps 3–6 to obtain \(C^{r+1}_m(r)\), theoretically, when the sequence length \(N\) is a finite value and the sample entropy estimate of the signal time series at scale \(\tau\) is \(SE(\tau, m, r) = -\ln \left( C^{r+1}_m(r) / C^r_m(r) \right) \).

(8) The multi-scale entropy MSE of the magnetic signal sequence is the set of sample entropy at multiple scales:
\[
MSE = \left\{ \tau \mid -\ln \left( C^{r+1}_m(r) / C^r_m(r) \right) \right\}.
\]

The value of MSE is related to the value of \(m\) and \(r\); generally, \(m = 2\), and \(r = 0.1\) to 0.25 times the standard deviation of the original sequence \(\{x_1, \ldots, x_n, \ldots, x_N\}\). The calculation process of the multi-scale entropy value of \(K\) is the same as that of \(H_p(y)\).

2.2. Acoustic Emission Feature Extraction Method. When the component is subjected to cyclic loading, its internal fatigue micro-damage events such as dislocations, cyclic slip, and micro-crack initiation will cause the release of energy and produce transient elastic waves, which are collected by acoustic emission sensors and transformed into acoustic emission signals. Acoustic emission signals include ringing count, energy, and amplitude. In order to extract the characteristics of the above parameters, the accumulated ringing count is obtained by summing the ringing count values obtained in each fatigue damage stage, and the wavelet packet decomposition and singularity index methods are selected to extract the acoustic emission energy and amplitude signal characteristics, respectively.

The wavelet packet can decompose the acoustic emission energy signal into multiple frequency bands to obtain the energy spectrum on different frequency bands, and the time-frequency resolution can be improved by further decomposing the high-frequency part that cannot be subdivided by multi-resolution analysis. Figure 1 presents the schematic diagram of the decomposition structure of 2-layer wavelet packet, in which A indicates the low frequency, D indicates the high frequency, and the serial number is the number of decomposition layers.

The wavelet packet decomposition process is described as follows.

Let the expression of the real number space \(L^2(\mathbb{R})\) be as follows:
\[
L^2(\mathbb{R}) = \cdots \oplus W_{-1} \oplus W_0 \oplus W_1 \oplus \cdots = \oplus W_j, V_j \in \mathbb{Z},
\]
where \(j\) is the scale factor and \(W_j\) is the wavelet subspace. \(V_j\) is uniformly represented by a new subspace \(U^0\). \(V_j\) is the dimension space, and \(W_j\) is the wavelet subspace. Define \(U^0\) as the closure space of the function \(u_n(t), u_n(t)\) as the closure space of the function \(u_{2n}(t); u_{2n}(t)\) satisfies the dual scale equation. The expression is as follows [23]:
\[
\begin{align*}
&u_{2n}(t) = \sqrt{2} \sum_{k \in \mathbb{Z}} h(k) u_n(2t - k), \\
u_{2n+1}(t) = \sqrt{2} \sum_{k \in \mathbb{Z}} g(k) u_n(2t - k).
\end{align*}
\]

In the formula, \(g(k) = (-1)^k h(1 - k)\). Let \(\{u_n(t)\}_{n \in \mathbb{Z}}\) be the orthogonal wavelet packet of the orthogonal scaling function \(\varphi(t)\), and \(\langle u_n(t - k), u_n(t - 1) \rangle = \delta_{k1}\). Then \(\{u_n(t)\}_{n \in \mathbb{Z}}\) constitutes the orthogonal basis of \(L^2(\mathbb{R})\).

Wavelet packet decomposition is to find \(\{d^{j+1,n}_i\}\) and \(\{d^{2j+1,n}_i\}\) from \(\{d^{j+n}_i\}\).
\[
\begin{align*}
d^{j+1,n}_i &= \sum_k a_{k-2j} d^{j+1,n+1}_k, \\
d^{2j+1,n}_i &= \sum_k b_{k-2j} d^{j+1,n+1}_k.
\end{align*}
\]

Wavelet packet reconstruction is to find \(\{d^{j+n}_i\}\) from \(\{d^{j+1,n}_i\}\) and \(\{d^{2j+1,n}_i\}\).
\[
d^{j+n}_i = \sum_k [h_{-2j} d^{j+1,n}_k + g_{-2j} d^{2j+1,n}_k].
\]

Let \(f\) be the acoustic emission energy signal, and decompose the collected signal \(f\) at layer \(i\) to obtain the wavelet packet energy spectrum as follows:
\[
E_i = \{E_{i,p}\} = \left\{ \left| f_{i,p} \right|^2 \right\}, \quad (p = 0, 1, \ldots, 2^i - 1),
\]
\[
I_p = \frac{E_{i,p}}{\left( \sum_{i=0}^{2^i-1} E_{i,i} \right)^{2/p}}, \quad (p = 0, 1, \ldots, 2^i - 1)
\]

where \(E_i\) is the wavelet packet energy spectrum vector, \(i\) is the hierarchical level, and \(I_p\) represents the energy ratio on each frequency band.

The singularity index can be used to describe the singularity characteristics of the acoustic emission amplitude signal in fatigue process. Specific steps are as follows [24].

At a certain point \(x_0\), there exists a constant \(K_i\), so that the following inequation holds at any point in a neighborhood of \(x_0\):
\[
|f(x) - f(x_0)| \leq K_i |x - x_0|^r.
\]

Then, the function \(f(x_0)\) has a consistent singularity index at \(x_0\). At scale \(s_0\), the following inequation holds for any point in a neighborhood of \(x_0\):
Advances in Materials Science and Engineering

Let the feature $x_i$ obey the normal distribution under the damage category $c_i$; calculate prior probability $P(x_i|c_i)$ of the model as

$$P(x_i|c_i) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_i - \mu)^2}{2\sigma^2}\right).$$

In the above equation, $\mu$ denotes the mean value of the $i$-th dimensional feature in the sample of category $c_i$. $\sigma^2$ represents the variance of the $i$-th dimensional feature in the sample of the category $c_i$, where $i = 1, 2, 3, ..., N$ is the number of training samples.

$$\mu = \frac{\sum_{i=1}^{N} x_i}{N},$$

$$\sigma^2 = \frac{\sum_{i=1}^{N} (x_i - \mu)^2}{N}.$$

According to the Naive Bayes formula, for the posterior probability values of different categories $c_i$, the denominator of the Bayes formula remains the same, so only the numerator needs to be solved. Taking class $c_1$ as an example, the posterior probability formula is as follows:

$$P(c_1|x_i) = P(c_1) \cdot \prod_{i=1}^{n} P(x_i|c_1) (i = 1, 2, 3...).$$

In the above Gaussian Naive Bayes model, the mean and variance of the magnetic-acoustic features of each fatigue damage stage are taken as prior information, and the probability density value is calculated using the probability density function formula. Then, the posterior probability corresponding to each damage category is calculated based on the test data of magnetic memory and acoustic emission features, and the category corresponding to the maximum posterior probability is selected as the prediction result.

3. Materials and Procedures

3.1. Experimental Materials. The same batch of 45 steel specimens was selected as the research object, and the
specimen blanks were fabricated by laser cutting. The material composition of the specimens is shown in Table 1, and the dimensions are shown in Figure 3.

3.2. Experimental Platform and Procedure

3.2.1. Experimental Platform. The electrohydraulic servo fatigue testing machine (SDS-200, Sinotest Equipment Co., Ltd.), intelligent magnetic memory diagnostic instrument (EMS-2000+, Eddysun (Xiamen) Electronic Co., Ltd.), and acoustic emission system (SAEU3H, Beijing Shenghua) were selected to build the experimental platform for detecting the magnetic-acoustic characteristics of the fatigue damage process (Figure 4).

3.2.2. Experimental Procedure. The 45 steel specimens were demagnetized to keep their initial magnetic state consistent. A strain-controlled method was adopted to apply cyclic loads to specimens with load amplitude of 1 mm and frequency of 5 Hz. With an interval of 1000 cycles, when the fatigue cycles were 1000, 2000, 3000, 4000, ..., until fracture, the specimens were unloaded and removed for magnetic memory testing. The acoustic emission signals were collected in real time during the whole fatigue test, i.e., the acoustic emission signal corresponding to the six stages with fatigue cycles of 0–1000, 1000–2000, 2000–3000, 3000–4000, 4000–5000, and 5000–fracture. The magnetic memory detection path is shown as line a-b in Figure 3, and the layout positions of acoustic emission sensors are shown as AE-1 and AE-2 in Figure 3. The initial magnetic memory and acoustic emission signals were obtained through the magnetic memory and acoustic emission detection experiments of 45 steel specimens in fatigue damage process, and the characteristics of $H_p(y)$ and its multi-scale entropy, $K$ and its multi-scale entropy, cumulative ringing count, acoustic emission energy spectrum, and amplitude singularity index were extracted. Then, the magnetic-acoustic feature fusion and damage assessment model was constructed based on the Gaussian naive Bayesian method.

4. Results

4.1. Magnetic Memory Feature Extraction. The variation curves of $H_p(y)$ for each fatigue damage stage are shown in Figure 5. The abscissa in the figure is the data acquisition point, which corresponds to the detection path a-b (Figure 3). The zero-value point of $H_p(y)$ curves is located at the center of the specimen, and its position identifies the stress concentration region. With the increase of fatigue cycles, the absolute value of $H_p(y)$ gradually increases. In the fatigue fracture stage, the $H_p(y)$ value is reversed, and the absolute value of $H_p(y)$ near the fracture increases notably, which is related to the significant changes in dislocation density and pinning energy of the material in the fatigue fracture stage.

The multi-scale entropy method was used for magnetic memory feature extraction, and the multi-scale entropy of $H_p(y)$ was obtained (Figure 6). It can be seen from the figure that the multi-scale entropy of $H_p(y)$ generally increases with the increase of scale factor, especially in the middle and late stages of fatigue damage. With the increase of fatigue cycles, multi-scale entropy of $H_p(y)$ gradually increases, and the highest multi-scale entropy value is found in the fracture stage. The average value of 10 multi-scale entropy values corresponding to each fatigue damage stage is taken as the characteristic parameter, which is denoted as MSE($H_p(y)$)avg. Figure 7 is the variation curve of MSE($H_p(y)$)avg in fatigue damage process, and MSE($H_p(y)$)avg shows an increasing trend with the increase of fatigue cycles.
Figure 8(a) shows the \( K \) curve when the fatigue cycle is 1000–5000, and Figure 8(b) is the \( K \) curve for the fracture stage. The \( K \) curve has a peak value at the zero-value point of \( H_p(y) \) (i.e., stress concentration position), which is recorded as \( K_{\text{max}} \). In the initial stage, the \( K \) value has no obvious change trend. The value of \( K_{\text{max}} \) increases significantly in the late stage of fatigue damage, and \( K_{\text{max}} \) reaches the maximum value at fracture.

Figure 9 shows the variation curves of \( K \) multi-scale entropy for each fatigue damage stage. It can be seen that with the increase of the scale factor, except for the fracture stage, \( K \) multi-scale entropy shows a trend of first increasing and then decreasing. The average value of 10 multi-scale entropy values corresponding to each fatigue damage stage is adopted as the characteristic parameter, which is recorded as \( \text{MSE}(K)_{\text{avg}} \). The change curve of \( \text{MSE}(K)_{\text{avg}} \) in fatigue process is shown in Figure 10, and \( \text{MSE}(K)_{\text{avg}} \) gradually decreases with the increase of fatigue cycles.

4.2. Acoustic Emission Feature Extraction. Three types of signals, acoustic emission ringing count, energy, and amplitude are selected for feature extraction. During the experiment, the waveform and parameter threshold value of acoustic emission were set to 50 dB in order to filter the interference signal generated by the laboratory environment noise. Figures 11(a)–11(c) show the original signals of acoustic emission ringing count, energy, and amplitude during fatigue, respectively.

As seen in Figure 11(a), the ringing count values show a decreasing trend with the increase of the number of signals, indicating that as the degree of fatigue damage increases, the number of signals collected by the acoustic emission equipment which exceeds the threshold value gradually decreases. This is related to the cyclic softening phenomenon of the specimen under low cycle fatigue loading and the gradual reduction of material stress. In addition, the signals of acoustic emission energy can characterize the elastic energy released by the acoustic emission event, which can be used numerically to describe the amount of energy released by the fatigue damage source. As shown in Figure 11(b), the acoustic emission energy shows a gradual upward trend with the increase of acoustic emission signals. Due to the presence of inclusions and minor defects inside the 45 steel
specimens, there exists some sudden increase peak signals in Figure 11(b). Figure 11(c) shows that the acoustic emission amplitude changes irregularly with the increase of fatigue cycles. Due to the presence of inclusions and minor defects, the acoustic emission amplitude also produces sudden increase peak signals.

In order to extract the characteristics of the abovementioned ringing count, energy, and amplitude, the ringing count values of each fatigue damage stage (such as fatigue cycles 1–1000, 1001–2000, 2001–3000,...) were summed to obtain the cumulative ringing count values, and the acoustic emission energy signals of each fatigue damage stage were decomposed by wavelet packet energy spectrum method. The 8 frequency band signals of acoustic emission energy were obtained by 3-layer decomposition. Since frequency band 1 has the highest proportion, the proportion of frequency band 1 of the energy spectrum was used as the characteristic parameter of acoustic emission energy. In addition, the singularity index of the acoustic emission amplitude of each fatigue damage stage was extracted and used as the characteristic parameter to describe the acoustic emission amplitude signal.

Figure 12 presents variations of the cumulative ringing count, the proportion of frequency band 1 of the energy spectrum, and the amplitude singularity index, which indicate that the cumulative ringing count and the proportion of frequency band 1 decrease with the increase of fatigue cycles, while the amplitude singularity index tends to increase.

4.3. Fatigue Damage Assessment of 45 Steel Specimens Based on Magnetic-Acoustic Feature Fusion. Based on the multi-scale entropy of magnetic memory signals and the cumulative ring count, the energy spectrum (the proportion of frequency band 1), and the amplitude singularity index characteristics of acoustic emission signals, the Naive Bayes method is adopted to construct the magnetic-acoustic feature fusion and damage assessment model.

Taking the damage state corresponding to 1000 fatigue cycles as an example, the mean and variance of each magnetic-acoustic feature were calculated, and the probability density function values of the feature parameters were obtained as the prior information values (Table 2). Figure 13 shows the probability density diagram of magnetic-acoustic feature parameters for each fatigue cycle (1000, 2000, 3000, 4000, 5000, and fracture).

Table 3 shows 6 groups of test data corresponding to each fatigue damage state. The posterior probability values of the test data are obtained based on the prior information of the magnetic memory and acoustic emission training data, as shown in Table 4.

Table 4 lists all the posterior probability values corresponding to each fatigue damage state for each set of test data, and the fatigue damage state corresponding to the maximum value of the posterior probability is taken as the damage assessment result. All the predicted results of the 6 groups of test data are correct, and the model can be used for the fusion assessment of magnetic-acoustic characteristics of the fatigue damage.
5. Discussion

In this paper, the magnetic memory and acoustic emission signals of the fatigue process of carbon steel specimens were extracted. It is found that $H_p(y)$ has a zero-value point and $K$ has a peak value at the micro-damage/stress concentration location. As the degree of fatigue damage increases, the absolute value of $H_p(y)$ gradually increases, and the values of $H_p(y)$ are reversed at the fatigue fracture stage. The cumulative ringing count values of acoustic emission gradually decrease with the increase of damage degree, while the acoustic emission energy shows an upward trend. To achieve fatigue damage assessment, the features are extended from the perspective of scale factor, wavelet packet energy spectrum, and singularity on the basis of the above signals, and the magnetic and acoustic features obtained show good regular changes.

Magnetic memory and acoustic emission signals of the fatigue damage process are derived from the detection of the leakage magnetic field and vibration wave of the specimen. The material of the specimen is subjected to cyclic loading, and minor internal-damage incidents such as dislocations and cyclic slip are formed. In the above-mentioned micro-damage region, the internal friction mechanism is complex, and the stress energy is high. Magnetic domains induced by magnetomechanical effects are reoriented and aligned to form magnetic poles, generating a leakage field on the surface of the component. In addition, dislocations moving...
along the slip direction need to cross the Peierls barrier, which is in the high-energy state, and when the dislocation moves from the Peierls barrier to the next low-energy position, the lattice elastic strain energy is released, and lattice waves are generated inside the material. It can be seen that the magnetic and acoustic characteristics have the same origin of damage.

The microscopic mechanisms of the change of magnetic and acoustic features—such as the correlation mechanism between the change of microscopic magnetic domain
Figure 12: Variations of the cumulative ringing count, the proportion of frequency band 1, and the amplitude singularity index.

Table 2: Mean value and variance of the magnetic-acoustic feature parameters (1000 cycles).

<table>
<thead>
<tr>
<th>Feature parameters</th>
<th>Mean value</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative ringing count</td>
<td>1094775</td>
<td>11659</td>
</tr>
<tr>
<td>Energy (proportion of frequency band 1)</td>
<td>43.5</td>
<td>0.389</td>
</tr>
<tr>
<td>Amplitude (singularity index)</td>
<td>0.1</td>
<td>0.0172</td>
</tr>
<tr>
<td>MSE($H_p(y)$)avg</td>
<td>0.02</td>
<td>6.67 × 10^{-5}</td>
</tr>
<tr>
<td>MSE($K$)avg</td>
<td>0.99014</td>
<td>9.86 × 10^{-6}</td>
</tr>
</tbody>
</table>

Figure 13: Continued.
Figure 13: The prior probability distribution of the magnetic-acoustic feature parameters for each fatigue damage state. (a) Cumulative ringing count. (b) Energy (proportion of frequency band 1). (c) Amplitude (singularity index). (d) MSE($H_p(y)$) avg. (e) MSE(K) avg.

Table 3: Six groups of test data for each damage state.

<table>
<thead>
<tr>
<th>Number of fatigue cycles</th>
<th>Cumulative ringing count</th>
<th>Energy (proportion of frequency band 1)</th>
<th>Amplitude (singularity index)</th>
<th>MSE($H_p(y)$) avg</th>
<th>MSE(K) avg</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>1094893</td>
<td>44.5</td>
<td>0.2</td>
<td>0.01764</td>
<td>0.99675</td>
</tr>
<tr>
<td>2000</td>
<td>820452</td>
<td>38.95</td>
<td>0.25</td>
<td>0.0196</td>
<td>0.90543</td>
</tr>
<tr>
<td>3000</td>
<td>796568</td>
<td>36.5</td>
<td>0.3</td>
<td>0.02323</td>
<td>0.84234</td>
</tr>
<tr>
<td>4000</td>
<td>722547</td>
<td>35.9</td>
<td>0.35</td>
<td>0.02643</td>
<td>0.77129</td>
</tr>
<tr>
<td>5000</td>
<td>706241</td>
<td>31.3</td>
<td>0.5</td>
<td>0.03</td>
<td>0.67578</td>
</tr>
<tr>
<td>Fracture</td>
<td>457579</td>
<td>26.34</td>
<td>0.6</td>
<td>0.04532</td>
<td>0.1478</td>
</tr>
</tbody>
</table>
structure and magnetic features during fatigue damage, and the change rule of lattice waves due to the release of elastic strain energy by dislocation motion—are still scientific problems to be solved.

### 6. Conclusion

An experimental platform was built to detect the magnetic-acoustic features of fatigue damage process, and the magnetic memory and acoustic emission signals of fatigue damage process were obtained from 45 steel specimens. The magnetic-acoustic features were extracted, and the magnetic-acoustic feature fusion and damage assessment model was constructed.

1. In each fatigue damage state, the $H_p(y)$ curve has a zero-value point, and the $K$ curve has a peak value at the zero-value point of $H_p(y)$. The absolute value of $H_p(y)$ gradually increases with the increase of fatigue cycles. During the fatigue fracture stage, the $H_p(y)$ value is reversed, and the absolute value of $H_p(y)$ and the peak of $K$ increase significantly near the fracture. The multi-scale entropy of $H_p(y)$ increases with the increase of scale factor. With the increase of fatigue cycles, MSE($H_p(y)$)avg gradually increases, and MSE($K$)avg gradually decreases.

2. With the increase of fatigue cycles, the cumulative ring count of acoustic emission and the proportion of frequency band 1 of the energy spectrum decrease, while the singularity index of the amplitude gradually increases.

3. Taking MSE($H_p(y)$)avg, MES($K$)avg, cumulative ring count, energy spectrum (proportion of frequency band 1), and amplitude singularity index as input parameters and fatigue cycles as output parameter, we established a magnetic-acoustic feature fusion and damage assessment model based on the Naive Bayes method, and the model has high assessment accuracy.

### References


