Summary of Metal Fracture Image Recognition Method

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Abstract. Fracture is the metal component in the test or use of the fracture surface after the formation of a matching section. In fracture analysis, the macroscopic and microscopic morphology of fracture provides the most direct information for failure analysis and the most direct evidence for fracture analysis. How to effectively process a series of feature information contained in fracture image and make reasonable use of these feature information is of great significance in engineering practice. At present, metal fatigue failure detection in industrial production mainly relies on human eyes, experience and simple auxiliary tools. However, it is difficult to guarantee the accuracy of detection because of individual differences. To solve this problem, this paper lists three metal fracture image recognition methods, which are Grouplet-RVM recognition method, the empirical Ridgelet-2DPCA method and the empirical Ridgelet-KPCA method. All the three methods aim to extract higher recognition effect so as to compare and optimize the recognition of metal fracture images. The advantages and disadvantages of these methods are discussed in detail in this article for ease of use.

Keywords: recognition methods, feature extraction, metal fracture, image processing.

1. Introduction
Fracture analysis [1] is a subject that studies metal fracture surface and is a component of fracture discipline. It runs through all stages of fracture failure analysis and involves many aspects of fracture failure analysis. It is the core of fracture failure analysis. After the fracture of a metal part, the plastic deformation before fracture and the information of fracture process are left on the fracture surface. For a long time, People only through the observation method to qualitative and analysis. The pattern recognition of metal fracture is only based on the understanding of fracture knowledge and experiential mastery of technical personnel, but this is far from the actual needs. In recent years, because there is no timely and accurate determination of metal fracture mechanism, or even can not take timely and effective preventive measures, in the actual engineering often lead to the same accident happened again and again.

In production practice, fracture failure is the most harmful to all kinds of mechanical equipment, and fracture analysis is the most primary analysis tools in various fracture failure analysis techniques. After the occurrence of fracture, it is necessary to first determine the type and characteristics of fracture, and then quantitatively analyze other information of fracture. Therefore, how to conduct the correct intelligent classification and recognition of the acquired fracture images is the key problem for mechanical fault diagnosis and fracture analysis quantification.
This paper firstly introduces the research status of metal fracture image, and then lists three methods of metal fracture image processing, which are Grouplet-RVM recognition method, the experiential Ridgelet-2DPCA recognition method and the experiential Ridgelet-KPCA recognition method. The three methods are all for extracting higher recognition effect, and they all have their advantages and disadvantages in metal fracture image recognition.

2. Research status of metal fracture image processing

Metal fracture image processing is mainly studied from three aspects:

(1) Metal fracture preprocessing

In the process of fracture image preprocessing, there are mainly spatial domain image preprocessing, such as Texture analysis, Gray level co-occurrence matrix. And the processing of the transformation domain, such as Fourier transform, Gabor transform, wavelet transform. Many scholars have also done research on fracture image preprocessing, as well as the processing of the transformation domain, such as Fourier transform, Gabor transform and Wavelet transform. In particular, a new signal processing algorithm, Grouplet Transform, introduces the concept of correlation domain into the algorithm transform. This method was proposed by French scholar Mallat in 2008[2], and this reform makes Grouplet transform can associate a series of feature points in scale transformation. In image processing, the Grouplet transform can utilize the geometric texture structure of the image itself to adapt to the change base. This method is characterized by better sparseness and flexibility, and has certain advantages in image processing of fracture [3].

(2) Feature extraction of metal fracture image

For all kinds of metal fracture images, there are many different texture curve features, and certain algorithms can be selected to extract high quality features from the images. In texture feature extraction based on fracture image, signal processing methods in the transformation domain, such as Wavelet and Gabor transform, are still the most widely used and have reference significance. However, although they have made great achievements in image processing and feature extraction, they still need to be improved and perfected.

In recent years, an emerging empirical superwavelet method, such as two-dimensional empirical wavelet, empirical ridgelet and empirical curvewave transform algorithm, is a data-driven method. The algorithm itself has certain self-adaptability and has better performance than Grouplet transform. In the process of image processing, an appropriate wavelet framework can be constructed according to the geometric features of the image itself, and the low frequency information and various modes of the high frequency information can be decomposed adaptively at each scale to extract and select the features of the low frequency and high frequency information. In order to improve the recognition rate of fracture images and obtain better results of fracture classification, researchers need to continue to expand and improve the algorithm. Such empirical super wavelet transform may be a potential development direction, which is worth further exploration [3].

(3) Metal fracture image recognition

The pattern recognition process of metal fracture images mainly has two key problems: one is to have an excellent feature extraction system of fracture; the other is to choose an effective learning model such as classifier, so as to be able to carry out high recognition rate image recognition of metal fracture images. At present, the commonly used time domain analysis methods include gray level co-occurrence matrix method [4], syntactic pattern recognition [5], neural network, fractal and so on. Instead of selecting and classifying all the extracted image features, and finally loading them into the classifier for image recognition, it is to fit multiple features.

In addition, in the metal fracture image pattern recognition and classification algorithm, there are fuzzy algorithm [6], neural network algorithm, C and its extension algorithm [7], nearest neighbor classifier algorithm [8], decision tree classifier algorithm and so on. However, they also more or less have certain deficiencies. For example, Support Vector Machine needs to choose an effective kernel function, when faced with large sample data, it is likely to appear the phenomenon of over-fitting, or computing time and speed have been reduced.
3. Metal fracture identification method

3.1. Based On Grouplet-RVM Recognition Method

Grouplet transform is a new image multi-scale analysis technology proposed by Mallat in 2008, which can realize a fast algorithm of two-dimensional image processing through Haar transform, and its superior performance is much better than the existing wavelet analysis methods and other directional wavelets. In view of the shortcomings of the wavelet transform method in the image recognition of metal fracture, Dr. Zhinong Li introduced the idea of ultra-wavelet analysis into the image processing of metal fracture and carried out in-depth research [9]. Because Grouplet Transform has a new theoretical outlook and unique application characteristics, especially in processing images with rich texture information. Grouplet transform is introduced into metal fracture image processing, and the unique advantages of Grouplet transform are utilized to extract the features of metal fracture image. In combination with correlation vector machine, a Grouplet transform based RVM recognition method for metal fracture images is presented.

1) RVM Function

If the training sample is \( \{ x_i, t_i \}_{i=1}^{N} \), \( x_i \) is the feature data to be classified, \( t_i \in \{0,1\} \) is the recognition output target, then the prediction function can be obtained as:

\[
y(x, w) = \sum_{i=1}^{M} w_i K(x, x_i) + w_0
\]

Where:
\( M \) = the number of kernel functions.
\( K(x, x_i) \) = kernel function.
\( \{ w_i \} \) = the weight of the correlation vector.
\( w_0 \) = initial weight values.

Relevance Vector Machine infer the above weights under the framework of complete probability. In order to avoid over-learning of the optimal value \( w \), the Sparse Bayesian method directly adds a constraint of conditional probability distribution to the weight parameter, so that \( w_i \) obeys the normal distribution \( N(0, \alpha_i^{-1}) \), and the likelihood function of the whole sample is:

\[
P(c_i | a, \sigma^2) = \left( \frac{2\pi \sigma^2}{\sigma^2} \right)^{\frac{N}{2}} \exp \left[ -\frac{1}{2\sigma^2} \left( t_i - \eta \right)^2 \right]
\]

If \( B = [\eta(x_1), \eta(x_2), \ldots, \eta(x_N)] \), the Relevance Vector Machine function can be written as:

\[
f(x) = B'(x) \left[ \sum_{i=1}^{N} a_i B(x_i) \right]
\]

2) Specific Step

The specific steps of fracture image recognition using RVM are as follows:

a) The radial basis function RBF is selected as the kernel function to map the characteristic data to a high-dimensional space, where the RBF function is:

\[
K(x, x_i) = \exp \left( -\frac{\| x - x_i \|^2}{2\sigma^2} \right), \sigma > 0
\]

\[
\alpha_i^{new} = \frac{\alpha_i}{\mu_i^2} = \frac{1 - \alpha_i \sum_{i,j} \mu_{ij}}{\mu_i^2}
\]

Where:
\( \sum_{ij} \) = the diagonal element of \( \Sigma \).
b) The estimated value of parameter $\alpha$ was obtained through multiple iterative optimization:

$$\sum = (B^T AB + \alpha)^{-1}$$

$$A = \text{diag}[y_1, (1 - y_1), \cdots, y_N, (1 - y_N)]$$

(6)

(7)

c) The classified data were calculated by formula $f(x) = B^T(x) \left[ \sum a_i B(x_i) \right]$, and the obtained data were predicted and classified.

The metal fracture identification method based on Grouplet-RVM is shown in Fig. 1.

![Figure 1. Grouplet-RVM Recognition Method](image)

This method mainly includes two important processes, one is the feature extraction of the fracture image, the other is the establishment of the recognizer. The Grouplet average energy is the average reflection of the texture information of the fracture image. In the aspect of texture features, kurtosis is more sensitive than average energy, which is more conducive to feature extraction of fracture images. The recognizer uses RVM proposed by Tipping[10], which has a fast recognition method and strong algorithm generalization ability. The Grouplet transform can take place in any space and time, and the geometric features of the image can be extracted to the maximum extent. Therefore, the Grouplet-RVM recognition method has a good recognition effect. However, the algorithm of RVM also has some shortcomings. There is no standard for kernel function selection, and improper selection will have a great impact on the results.

Grouplet-RVM method can overcome the shortcomings of wavelet-RVM method. Grouplet transform breaks through the limitation of multi-scale image decomposition, can be transformed in any
time and space, and has the ability to change the base adaptively according to the texture structure of
the image, and can make maximum use of the geometric features of the image. Therefore, the Grouplet-
RVM recognition method achieves better recognition effect than the wavelet -RVM recognition method.
Compared with the Grouplet-SVM method, the Grouplet-RVM method uses far less support vectors
than the Support Vector Machine (SVM) while the recognition accuracy is basically unchanged.
Therefore, the recognition method is faster, especially with the increase of training samples. Grouplet-
RVM recognition speed advantage is more obvious.

3.2. Based On The Empirical Ridgelet-2DPCA Recognition Method

The core idea of the empirical Ridgelet transform is to divide the normalized spectrum by extracting
the maximum points in the frequency domain, and then establish a set of filters according to the divided
spectrum. Finally, the image will be decomposed into a group of independent BIMF components after
the empirical Ridgelet transform. Based on the excellent characteristics of ultra-wavelet analysis in
metal fracture image feature extraction, Gilles J proposed the empirical Ridgelet transform based on the
Ridgelet theoretical framework and the construction idea of empirical wavelet.

The essence of Ridgelet transform is to add direction parameter on the basis of wavelet
transform. Therefore, Gilles J regards Ridgelet transform as the set of one-dimensional signals and the
wavelet transform in all directions [11]. The idea of constructing empirical Ridgelet transform can be
realized through empirical wavelet [12].

1) The Experience Ridgelet Transform Algorithm

a) Input image signal \( f(x_1, x_2) \) to determine the number of filters \( N \).

b) Calculate the pseudo polar fast Fourier transform \( F(\omega, \theta) \) of the image, averaging it with respect
to \( \theta \):

\[
F(\omega) = \frac{1}{N_\theta} \sum_{\theta=0}^{N_\theta-1} F(\theta, \omega)
\]  

(8)

c) The segmentation interval of \( F(\omega) \) is obtained by the edge detection algorithm:

\[
\Delta_n = [\omega_{n-1}, \omega_n], \ n = 1, 2, \cdots, N
\]  

(9)

\[
Y_{n=1}^{N} \Delta_n = [0, \pi]
\]  

(10)

d) Determine the segmentation interval \( \Delta_n \), and use the formula to establish the filter window
function \( B_{\phi} = \{ \phi(x), \phi'(x) \}_{n=1}^{N+1} \).

e) The input image is filtered according to the filter window function established in Step 4, and the
BIMF component of the image signal can be output.

2) Specific Step

In the empirical Ridgelet-2DPCA recognition method, the three steps of optimal mode extraction,
2DPCA dimension reduction and classification method are very important, as shown in Fig.2. First, the
optimal mode is the one with the maximum entropy of empirical Ridgelet, and then the eigenvectors
were obtained by 2DPCA dimension reduction, and the classification method was the nearest neighbor
classification.

The empirical Ridgelet transform has the ability of directional selectivity and adaptive
decomposition, as well as higher recognition rate, which proves the effectiveness of the proposed
algorithm. Since the wavelet transform can only obtain the feature information of the port image in a
limited direction, its disadvantage is reflected when the geometric structure of the selected image is
relatively complex.
Compared with the empirical Ridgelet-2DPCA and the empirical Ridgelet-PCA recognition methods, the eigenvectors are the same, but the dimension reduction methods are different. 2DPCA uses the image matrix to construct the covariance matrix, which retains the structural information of the original image, and its covariance matrix estimation is more accurate, thus achieving a higher recognition rate. Moreover, the time complexity required by experienced Ridgelet-2DPCA to calculate the corresponding eigenvalues and eigenvectors is less. The experimental results show that the proposed method is effective [13].

3.3. Based On The Empirical Ridgelet-KPCA Recognition Method

Principal component analysis (PCA) is a linear projection method, which has a good effect on extracting linear feature data. However, because the feature information of the image is often nonlinear, when PCA is used, the high-order nonlinear feature information related to the image may be lost. Therefore, KCPA is a nonlinear generalization of PCA.

Combining the advantages of kernel function and PCA, KPCA firstly maps the metal fracture image data set in the input space to the high-dimensional feature space in a nonlinear way, and then carries out linear PCA on the data set in the high-dimensional feature space to extract the high-order nonlinear feature information of the data.

1) KPCA Algorithm Description

Input: metal fracture image sample training set \( \{x_i\}_{i=1}^{N} \)
Process:

a) The kernel matrix of metal fracture image sample training set is calculated as 
\[ K = \{K(x_j, x_i)\} \]
\[ K(x_j, x_i) = \phi^T(x_j)\phi(x_i) \]  
(11)

Where: The size of the kernel matrix \( K \) is \( N \times N \).

b) Computing eigenvalue
\[ K\alpha = \lambda\alpha \]  
(12)

Where:
\( \lambda \) = The eigenvalues of the kernel matrix \( K \).
\( \alpha \) = The corresponding eigenvector.

c) Normalize the calculated eigenvalues
\[ \alpha_k^T\alpha_k = \frac{1}{\lambda_k}, k = 1, 2, \cdots, p \]  
(13)

d) Calculate the projection
\[ \alpha_k = q_k^T\phi(x) = \sum_{j=1}^{N}\alpha_{k,j}K(x_j, x_k), k = 1, 2, \cdots, p \]  
(14)

Where:
\( \alpha_{k,j} \) = The Jth member of eigenvector \( \alpha_k \).

2) Specific Step

a) Three types of characteristic quantities of fracture image empirical Ridgelet entropy, empirical Ridgelet average energy and empirical Ridgelet kurtosis are obtained.
b) Extract the principal components of the obtained feature vector.
c) To determine the category of the sample to be tested, the specific process is shown in Fig.3.

![Figure 3. Experience Ridgelet-KPCA Recognition Method](image-url)
Since the classical PCA is a linear algorithm, when there is linearly inseparable feature information in the data, PCA cannot extract it effectively, while KPCA can extract the feature information of the original data set. Under the same recognition method, the recognition results using empirical Ridgelet kurtosis as the feature vector are significantly better than those using empirical Ridgelet average energy and empirical Ridgelet entropy.

The results indicate two points: One is the sensitivity of experiential Ridgelet kurtosis to the change of fracture texture features is higher than experiential Ridgelet average energy and experiential Ridgelet entropy; the other is the empirical Ridgelet kurtosis is the fourth power relation of the empirical Ridgelet coefficient, which reflects the high-order nonlinear characteristic information of the image. KPCA can extract the nonlinear feature information of fracture image effectively [13].

4. Summary
This paper summarizes three methods for the identification of metal break images, and discusses their advantages and disadvantages. The research work on the method of broken image recognition is mainly manifested in three aspects: the feature extraction of the broken image, the compression of the feature space of the image, and the selection of classification method. These three aspects correspond to many methods, they are combined and applied, we will get a new metal break image recognition method, through the experimental results to choose more convenient, higher recognition effect of the method. Through the observation and analysis of the appearance of the broken mouth, we can obtain a lot of useful information, but also can avoid the occurrence of similar accidents.

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