Intelligent recognition of defects in vermicular graphite cast iron engine cylinder head by ultrasonic testing

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Abstract—To detect and intelligently identify the defects of the vermicular cast iron cylinder head, defective casting samples were made corresponding to each type of the actual defects. We setup the ultrasonic testing system to examine the defective samples. The detected defect signals were processed to obtain the characteristic spectrograms of the defects, which were further sorted and classified into a sample database. An algorithm based on a convolutional neural network was proposed to identify the defects intelligently. A convolutional neural network model was established. The network structure and parameters were optimized. It shows that a neural network with 3×3 convolution kernel dimension, 3 convolution layers, 20 convolution kernels in each layer and a learning rate of 0.0005 can effectively identify the spectrograms of the defects. The results show that the identification accuracy of the proposed algorithm is 97.14%. The model meets the practical requirements of cylinder head defect detection. The detection efficiency has improved significantly.

1. Introduction

With the development of science, the performance requirements of the engine are constantly improving, and the specific power and combustion pressure of the engine, as well as the working temperature of the engine block, are also significantly improved. There is a strong demand for new materials to improve engine performance [1]. As a new type of cast iron material, vermicular graphite cast iron is widely used...
in engine cylinder head and cylinder block because of its good thermal conductivity and shock absorption performance. However, due to the difficulty in the production process of cylinder block castings, defects such as air holes, loosen and shrinkage may occur in the process of raw material melting, molten iron melting creep treatment, pouring exhaust system and sand core gas precipitation, which seriously affect quality of the cylinder block [2].

The most common method to check the quality of vermicular graphite cast iron castings is to take samples for metallographic observation, but this method is destructive and cannot be used for large-scale inspection of all products. Non-destructive testing technology can carry out comprehensive and systematic testing of samples without damaging them. Among nondestructive testing methods, the X-ray method can detect defects in the structure with high accuracy. However, it has side effects, even has certain harm to the human body [3], and the cost is high. The ultrasonic testing method has the characteristics of a wide range of tested objects, deep detection, accurate defect location, high detection sensitivity, and no harm to human body. It can be used for rapid nondestructive testing of vermicular cast iron castings in large quantities [4,5].

Different kinds of defects may appear in the prepared materials. In order to study the material defects of vermicular graphite cast iron, the ultrasonic nondestructive testing technology can be used to detect the castings. Due to uncertainty of measurement, the signal will change with time, so it is difficult to obtain accurate eigenvalues directly. In order to extract defect features effectively, it is necessary to analyze the change domain of the signal. The Short-time Fourier transform (STFT) is a common method for time-frequency analysis of complex signals. The time-frequency characteristics of defects in the signal can be obtained by STFT.

At present, in practical application, after obtaining the ultrasonic detection signal of castings, professionals are required to manually analyze the signal characteristics according to experience to determine the type of defects [6]. In the process of nondestructive testing of castings, the amount of data is huge, which leads to a large amount of manual work. And the test results are affected by the subjective judgment of the tester to a certain extent. Image recognition and classification based on artificial intelligence technology can improve the detection efficiency and accuracy at the same time, which is of great significance to reduce the work intensity of detection personnel and reduce the accumulation of empirical work [7]. Convolution neural network is a deep learning method specially designed for image classification and recognition based on multilayer neural networks in recent years. Existing image feature extraction algorithms can be divided into traditional statistical feature extraction algorithms and intelligent extraction algorithms based on neural network [8]. Traditional algorithms are mainly suitable for computing local pixel data or extracting local texture features. Compared with the traditional algorithms, convolutional neural network can get high-level abstract features by inputting a large number of original data into the deep network through self-training [9-11].

To identify the defects of vermicular cast iron, an intelligent method for identifying the defects of vermicular cast iron based on convolutional neural network is proposed in this paper. Different kinds of defect samples of vermicular cast iron were prepared, and the defect signals were obtained by the ultrasonic testing system. The defect spectrograms were obtained by STFT, and the defect spectrogram sample database was obtained after sorting. Convolutional neural network is built to analyze the sample database of defect feature map. By changing the hyperparameters in the network structure, the influence of hyperparameters on the accuracy of defect recognition is studied. Experiments show that the intelligent recognition algorithm is reliable in vermicular cast iron defect recognition, and improves the recognition efficiency of different types of vermicular cast iron defects.

2. Experimental design

2.1. Sample Preparation

The vermicular cast iron engine cylinder head is shown in Fig. 1, and various defects will appear on the surface and inside of the material. Because the abnormal structure of the original defects of the cylinder
head will have a great influence on the ultrasonic detection signal, and the defects cannot be accurately detected, the vermicular cast iron samples were prepared to replace the original cylinder head castings.

![Image](image1.png)

Figure 1 Schematic diagram of vermicular cast iron engine cylinder head

In order to study various possible defects of vermicular cast iron materials, several samples with single hole, porous hole, loose and shrinkage defects (as shown in Fig. 2) and non-defect comparison samples were prepared. The test samples are vermicular cast iron casting materials with the same engine block and cylinder head.

Samples are single hole samples with end faces of 30 mm×35 mm and heights of 30 mm, 40 mm, 50 mm, 60 mm and 130 mm respectively distance between the hole and the end face is 15 mm, 20 mm, 25 mm, 30 mm and 75 mm respectively, and the diameter of a single hole is 10 mm, loose and shrinkage samples are made of vermicular cast iron which is the same as that of engine cylinder head. Loose and shrinkage cavity are produced inside the samples by casting.

![Image](image2.png)

Figure 2 Defective test samples (a) single hole (b) porous hole (c) loose (d) shrinkage

2.2. Test system

A set of A-scan ultrasonic testing system was established to test vermicular cast iron materials. It consists of vermicular cast iron castings, arbitrary function generator, power amplifier, transducers, oscilloscopes and computers. The ultrasonic testing system is shown in Fig. 3.

![Image](image3.png)

Figure 3 Schematic diagram of the ultrasonic testing experimental system

In the experiment, a 1.25MHz single transducer was used for detection, an arbitrary function signal generator was used for ultrasonic detection signal excitation, and RAM-5000 power amplifier was used to enhance the ultrasonic signal detection intensity. Ultrasonic waves are emitted by the transducer and enter the sample to be measured. When the ultrasonic wave encounters the internal defect of vermicular cast iron material, it will reflect a sound wave back to the receiving transducer. When the transducer receives the returned sound wave, it will convert it into the corresponding electrical signal, collect the
received signal through the oscilloscope, and finally the computer is used to analyze and process the signal collected by the oscilloscope.

2.3. Ultrasonic defect signal characterization spectrogram

Using the above-mentioned A-scan ultrasonic testing system, the vermicular cast iron samples with different types of defects are scanned by ultrasonic testing, and the defect signals of single hole, multi-hole, looseness and shrinkage hole are obtained, as shown in Fig. 4.

![Figure 4 Test signal of samples (a) normal (b) single hole (c) porous hole (d) loosen (e) shrinkage](image)

The ultrasonic A-scan is a waveform display. On the oscilloscope screen, abscissa represents time and ordinate represents the intensity of reflected waves. The severity of defect is roughly estimated according to the intensity of reflected wave, and the position of defect is calculated manually according to the position of reflected wave on the horizontal axis.

In order to obtain more intuitive defect information from the detected signal, short-time Fourier transform is performed on the detected signal to obtain the time-frequency features corresponding to defects in the signal.

Short-time Fourier transform is to add a sliding window with a fixed width on the time axis, because the window function can slide left and right, which makes the integration result contain both frequency information and time information, forming a time-frequency joint analysis. Defined as formula (1),

$$STFT_x(t, f) = \int x(\tau)g^*(\tau - t)e^{-j2\pi ft}d\tau$$

(1)

$x(\tau)$ is the source signal, and $g^*(\tau-t)$ is the window function.

The defect signal is subjected to short-time Fourier transform to obtain the defect spectrogram. The spectrograms of different defect types are shown in Fig. 5. The horizontal axis of spectrogram is time and the vertical axis is frequency. Different defects correspond to different image features in STFT spectrogram.
It can be seen that the spectrogram of different defects have obvious characteristics of different time and frequency. The features in the atlas are abstract, which requires manual analysis to judge the types of defects, and the detection results are influenced by the subjective judgment of the inspectors to a certain extent. The introduction of an intelligent recognition algorithm can complete the task of intelligent defect recognition and reduce the influence of subjective factors in human judgment.

3. Intelligent recognition algorithm

The intelligent identification process of defects of vermicular cast iron engine cylinder head is shown in Fig. 6.

![Flow chart of intelligent recognition for cylinder head defects of vermicular graphite cast iron engine](image)

Figure 6  Flow chart of intelligent recognition for cylinder head defects of vermicular graphite cast iron engine

The defect spectrograms were collected and the defect spectrogram sample database were obtained, the structure is optimized and adjusted. The network is trained to discriminate the samples, and the images is identified intelligently to output the recognition results.

3.1. Network architecture

Convolution neural network (CNN) structure includes input layer, convolution layer, pooling layer, full connection layer and output layer.

The convolution layer is composed of a plurality of feature maps, each of which is composed of a plurality of neurons, and each neuron of the convolution layer is connected with the local area of the feature surface of the upper layer through a convolution kernel. The convolution kernel is a weight matrix. CNN's convolution layer extracts different input features through convolution operation. The first convolution layer extracts low-level features such as edges, lines and corners, and the higher convolution layer extracts higher-level features.
Convolutional neural networks are characterized by local perception and weight sharing. Local perception is the local features obtained by local scanning at the bottom layer, and these features are synthesized at the top layer to obtain global information of the image. In CNN, the parameters in each convolution kernel are weights. After the original image is convolved, a new image will be obtained. Because the weights are shared, each pixel of the new image comes from the same convolution kernel.

The pooling layer is also composed of a plurality of feature maps, it follows the convolution layer, and is also composed of multiple feature surfaces, each of which uniquely corresponds to a feature surface of its upper layer, and the number of feature surfaces will not be changed. Convolution layer is the input layer of pooling layer, and one feature plane of convolution layer uniquely corresponds to one feature plane of pooling layer, and neurons of pooling layer are also connected with local acceptance domains of its input layer, and local acceptance domains of different neurons do not overlap. The pooling layer aims to obtain features with spatial invariance by reducing the resolution of feature maps. The pooling layer plays the role of secondary feature extraction, and each neuron of the pooling layer performs pooling operation on the local receptive field.

Each neuron in the fully connected layer is fully connected with all neurons in the previous layer. The full connection layer can integrate local information with class discrimination in convolution layer or pooling layer. In order to improve the performance of CNN network, the excitation function of each neuron in the full connection layer generally adopts RELU function. The output value of the last fully connected layer is passed to an output layer, which can be classified by softmax logistic regression. This layer can also be called softmax layer.

The convolution layer and pooling layer output advanced features of the input image, while the purpose of full connection layer is to classify the categories based on the training set with these features, connect all the features, and send the output values to the classifier (such as softmax classifier).

A constructed convolutional neural network (CNN) structure is shown in Fig. 7.

![Figure 7 Model structure of a typical layer convolution neural network](image)

The input matrix is [W1, H1] ultrasonic signal two-dimensional feature map. In order to realize the squareness of the two-dimensional matrix, the P padding factor is added in the x-axis direction of the image. The convolution kernel size is [F, F], and its offset strides along the x axis and y axis of the image is S. The size of the corresponding output layer can be determined by the convolution kernel number, convolution kernel size, padding and stride size, as shown in formula (2).

\[
\left\lfloor \frac{W + 2P - F}{S} + 1 \right\rfloor \times \left\lfloor \frac{H + 2P - F}{S} + 1 \right\rfloor
\]

where \(w\) and \(h\) represent the original image size; \(F\) represents convolution kernel dimension; \(S\) represents the convolution kernel moving strides; \(P\) stands for padding dimension.

3.2. Experimental environment
In MATLAB 2019 environment shown in Table 1, CNN programming framework is built. In the training process of convolutional neural network model, regularization constraint and penalty are added to optimize the whole convolutional network.
### Table 1 Experimental environment

| Test          | Configuration description   |
|---------------|-----------------------------|
| Hardware      |                             |
| CPU           | Intel(R) Core(TM)i5-750@2.67GHz |
| Memory        | 8GB                         |
| System        | Windows7                    |
| Software      |                             |
| Environment   | Matlab2019a                 |

3.3. Experimental data

The short-time Fourier transform maps of different kinds of defects (5 types, 462 images in total) obtained from the experiment are combined into a sample database, and the convolution neural network pairs are trained.

If the image size of the input layer is too large, it will increase the amount of computation, and it will need more data samples to obtain network convergence. However, if the image size is too small, the image cannot display complete signal information. Therefore, it is necessary to select the best resolution figure.

When dpi is low, the image is fuzzy and the defect information is unclear. When the image size becomes larger, the image accuracy improves. However, when the image size exceeds 300, image clarity tends to be stable and there is no significant change. In the experiment, the sampling frequency is 100MHz, the center frequency and sampling points of the signal are 1.25 MHz and 5000, respectively. According to the sampling theorem, the image pixels should be larger than 125. After comprehensive consideration, the defect signal image with the size of $225 \times 225$ is selected in the sample database.

4. Result analysis

Because the network structure of the convolution model is complex, even if GPU is used to accelerate network training, training time is relatively long, so it is necessary to find the most suitable network structure to obtain convolution model with strong robustness and small network loss. In the whole convolution model structure, the factors affecting the recognition rate and performance of the network model mainly include: convolution kernel dimension, number of layers, number of convolution kernels per layer, learning rate, etc. Therefore, different training parameters are used to find the convolution model with the best performance.

In order to study the influence of different dimensions of convolution kernel on the accuracy of model recognition. The discarding rate of activation function ReLU and Dropout of convolution network is 0.1, the learning rate is 0.0005, the number of convolution kernels in each layer is 20, and the related constraints remain unchanged. The dimensions of convolution kernel in the network are changed to $3 \times 3$, $4 \times 4$, $5 \times 5$ and $6 \times 6$ respectively. The curve of iteration times and accuracy is shown in Fig. 8. When the convolution kernel dimension is small, the accuracy of the results is high and LOSS value converges quickly. With the increasing dimension of convolution kernel, the accuracy gradually decreases and the result gradually does not converge.
With the increase of convolution kernel dimension, more pixel data need to be read in memory when traversing the whole signal image, which increases the computation of network and takes longer and longer time to train. It can be seen from Figure 9 that the 3 × 3 convolution kernel is more suitable.

When the learning rate is determined to be 0.0005 and the dimension of convolution kernel is 3 × 3, the influence of the number of convolution kernels in convolution layer on the accuracy of the model is studied. Set the convolution kernel number of each layer to be 10, 15, 20, 25 and 30 respectively. As shown in Fig.10, when the convolution kernel number of each layer is 20, the accuracy of the result is the highest. When the number exceeds 20, the precision decreases gradually.
After increasing the number of convolution kernels, the amount of computation of the network is increased, and training time becomes longer and longer. When the number of convolution kernels reaches 30, the computer runs stuck after the performance reaches the limit, resulting in a significant increase in computing time. Referring to the results of accuracy and calculation time, the effect is best when the number of convolution kernels in each layer is 20, as shown in Fig. 10.

When the learning rate, convolution kernel dimension and the number of convolution kernels per layer are fixed, the influence of convolution layers on the accuracy of the model is studied. Set the convolution layer number to 1-7. It can be seen that the accuracy is stable when the number of convolution layers is between 2 and 7, and it is easy to over-fit and fall into local optimum when the number of convolution layers exceeds 7. When the convolution layer is three layers, the accuracy is the highest and the LOSS convergence effect is the best, as shown in Fig. 11.

Under the condition of keeping convolution kernel dimension, convolution kernel number, convolution layer number, other parameters and related constraints unchanged, the influence of learning rate change on model accuracy is studied. Set the learning rate parameters in the network as 0.0005, 0.001, 0.002, 0.003 respectively. It can be seen from Fig. 12. When the learning rate is low, the convergence is obvious and the accuracy is high. With the increase in learning rate, the convergence decreases and even oscillation results appear. When the learning rate is 0.0005, the accuracy of the model is the best.
After optimizing the training model, finally, a convolution neural network model is built, which has the dimensions of 3×3 convolution kernels, 3 convolution layers, 20 convolution kernels in each layer, poling layer convolution kernels dimension 2×2 and a learning rate of 0.0005.

Table 2 Table of model training accuracy rate

| Epoch | Iteration | Time Elapsed (h:m:s) | Mini-batch Accuracy | Mini-batch Loss | Base Learning Rate |
|-------|-----------|-----------------------|---------------------|----------------|-------------------|
| 1     | 1         | 00:00:18              | 36%                 | 5.5917         | 0.0005            |
| 10    | 50        | 00:10:41              | 92%                 | 0.1735         | 0.0005            |
| 20    | 100       | 00:20:38              | 100%                | 0.0020         | 0.0005            |
| 30    | 150       | 00:30:36              | 100%                | 0.0003         | 0.0005            |
| 40    | 200       | 00:40:36              | 100%                | 0.0001         | 0.0005            |
| 50    | 250       | 00:50:36              | 100%                | 0.0001         | 0.0005            |

Accuracy: 0.9714

Enter the test set, and the accuracy of the test results (as shown in Table 2) reaches 97.14%, the model meets the requirements of intelligent recognition of vermicular cast iron cylinder head defects detection.

5. Conclusion
In this paper, the vermicular cast iron samples with different defects were examined by the ultrasonic nondestructive test. Signal processing was carried out on the acquired defect signal to obtain a defect characteristic spectrogram and generate a sample database. A convolutional neural network was built for intelligent recognition of the ultrasonic detection signal spectrogram sample database. To improve the performance of intelligent defect recognition network model, the hyperparameters in neural network structure were optimized. The main conclusions are as follows:

(1) A neural network of three-layer convolution layer architecture with convolution kernel dimension of 3×3 and convolution kernel number of each layer of 20 is adopted. This provides better accuracy and convergence performance. In the training process of the intelligent recognition algorithm model, when the learning rate is within the order of 10⁻⁴, the training accuracy is stable. The best learning rate was 0.0005. When the learning rate reaches 0.003, the result does not converge.

(2) The constructed convolutional neural network can intelligently identify the defects of the vermicular cast iron engine cylinder head, and the identification accuracy is 97.14%.

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