Nondestructive Detection of Ceramic Products Based on Tapping Sound Signal Feature Recognition

Liping Liu¹², Liucheng Jiang*, Lele Qiao¹

¹College of Artificial Intelligence, North China University of Science and Technology, Tang Shan, Hebei, 063000, China
²College of Mineral Engineering, North China University of Science and Technology, Tang Shan, Hebei, 063000, China
*Corresponding author’s e-mail: 11745430@qq.com

Abstract. Recent studies on the test of ceramic non-destructive testing are mainly based on high cost technologies, image processing and so on, these method possesses some drawback of low efficiency, high cost and so on. What’s more, detecting whether the ceramic products by human through listening to sound of tapping is also effectless. This paper proposed a non-destructive method for ceramic products to solve this problem. This non-destructive method consists of a tapping device and a signal processing module. The tapping device will be applied to generate the tapping sound signal and the signal processing system will be applied to analysis signal. After the process of signal analysis, sample length and peak of spectrum 2 parameters is extracted, then use these parameters to train SVM, the results will be compared with BP neural network (BPNN). The result of experiment shows that SVM with different kernels of linear, poly, rbf, sigmoid respectively reach the accuracy of 96.29%, 96.29%, 46.29%, 93.82%, while BPNN reaches the accuracy of 93.21%. This result proves that SVM can effectively complete the task of identifying defective ceramics, and its performance is better than BPNN.

1. Introduction

Ceramic industry is a traditional industry of China, Ceramic materials have good mechanical properties, thermal properties, electrical properties, and chemical properties [1]. However, ceramic product is a kind of fragile, the defect of ceramic products will affect its quality. And people require more and more high quality ceramic products. Therefore, detecting defective ceramic products is a very critical task for quality assurance in the production.

X-ray inspection, ultrasonic nondestructive testing, infrared thermography, acoustic emission, machine vision, terahertz technology and other traditional defect test technologies have been mainly used in the ceramics defective detection. Thornton et al. [2] analysis the failure of SiC ceramic matrix composite by applying micro X-ray CT technology. Sfarra et al. [3] compare two methods of advanced ceramic materials test. One is infrared thermography and another is holographic interferometry. Kesharaju et al. [4] select the defect feature from high frequency ultrasonic and use neural network to recognize defect. Zhao and Levikari. et al. [5-6] detect the damage of ceramics by using acoustic emission. Li et al. [7] apply sliding filtering and automatic region growing to detect the surface crack. Zhang et al. [8] detect the ceramic matrix composite insulation tile by using signal reflection method and bottom echo reflection method and examined cracks and holes successfully.

These detection technologies required high equipment cost and high technical requirements for operators, therefore, a lower cost and simpler technology are required to solve this problem. Coin-tap
test was first proposed by Adams [9], they identified the coin-tap model as a spring model, and provide a theoretical basis for this method. Wu H., Siegel M. [10] study a sensor which combines the force signal and sound signal and compare the feature of two kinds of signal to prove that the whole better than its parts, Philippe Duffour et al. [11] use vibration acoustic modulation method and use impact hammer to collect signals and extract the characteristics. Then they extract the interaction of vibration field and the correlation between crack size and modulation intensity. As a result, they successfully detect the large crack. Kim [12] established a spring model by FEM and compare the difference between force signal and voice signal and compare the influence of stretching and contracting, which perfected the theory of coin-tap test and illustrated that defects can be recognized by signal analysis, it can solve the problem of judging by artificial percussion. Mohd [13] The detection effect of different percussion instruments on CFRP plate is compared, and the damage location is determined by threshold discrimination, which reveals the consistency and accuracy of KETOK equipment. Xiao et al. [14] analysed the signal in time-frequency and judged the defect by threshold discrimination from duration and ratio of power spectrum peak and energy, prove that these method is effective. Zhang Tao et al. [15] tap some glass bottles to collect audio signals and extract signal feature of some frequency points and use mutual information to reduce the dimension of dataset. Finally, they use BPNN to realize automatic examining of glass bottles. Queiroz [16] detected polymeric resin by analysis acceleration signal and signal collected by microphone, and compared different time and frequency domain of different kinds of samples, they extract the peak of time domain and width of signal, peak frequency point of spectrum as the input of BPNN, and compare this result with the result of thermography, experiment proved the effectiveness of this method. Yu et al. [17] applied improved grey clustering, they considered the whole difference of time series to make grey clustering more accurate, and they proved their method is effective.

Compare some method of machine learning, neural network neural network needs many parameters, and the optimal parameters need to be adjusted many times. For the application scenario with large amount of data, neural network is more suitable. If the amount of data is not large, neural network may not be better than general machine learning algorithms and inefficiency. SVM is a powerful tool to complete the task of binary distinction and didn’t require large amount of data. We collect the audio signals by designing a tapping device to tap some completed ceramic products and by using computer to record the voice of tapping. Then FFT is applied to extract the features of these signals and to analysis these features. We compare the performance of BPNN and SVM to prove SVM can effectively to identify the defective ceramic products and its performance is better than BPNN.

2. Testing methods

2.1 Experimental setup
First of all, a tapping device was built to tap the ceramic products, voice generated by tapping was collected by MATLAB. Here shown a graphic of tapping device as Figure 1.
Here is the introduction of the tapping device.

1. The length of pendulum is 23 cm
2. The distance between initial position of pendulum and vertical position of pendulum is 7.5 cm
3. The distance between vertical position of pendulum and tapping position of pendulum is 5 cm
4. The distance between audio recorder and tapping position of pendulum is 10 cm

In MATLAB sound collection program, sampling frequency will be set as 44100 Hz, the length of record time is 4 seconds.

At last, 648 signal samples were collected, which include 324 samples by tapping defective ceramic products and 324 samples by tapping defectless ceramic products. In dataset which would be used to train classifier, defective label will be marked 0 and defectless label will be marked 1.

2.2. Signal intercept

It is necessary that the tapping sound part of the signal samples need to be intercepted in order to analysis these signal convenient. Here are 3 method to intercept: Short time energy threshold, short time zero crossing rate (ZCR) threshold and double threshold. The short time energy of every frame of signal $x_n(m)$ is expressed by equation (1).

$$E_n = \sum_{m=0}^{N-1} x_n^2(m)$$

Where $x_n^2(m)$ can be replaced by $\|x_n^2(m)\|$ to simplify the calculate. And $n$ is the ordinal of frame. And the equation (2) is applied to calculate ZCR of every frame of signal $x_n(m)$.

$$Z_n = \frac{1}{2} \sum_{m=0}^{N-1} [\text{sgn}(x_n(m)) - \text{sgn}(x_n(m-1))]$$

Where $\text{sgn}(x)$ is Symbolic function. In order to intercept the signal accurately, these 2 methods are often combined, which called double threshold.

2.3. FFT

Fast Fourier Transform (FFT) is origened form Discrete Fourier Transform (DFT), it’s important to analysis a signal. It expressed the finite sum of periodic complex exponentials. Compare to DFT, FFT only need to calculate the value of first half length of signal, which improve the efficiency of computing. The function of FFT can expressed as equation (3).

$$\begin{cases} X(k) = X_1(k) + W_N^k X_2(k) \\ X(N/2 + k) = X_1(k) - W_N^k X_2(k) \end{cases}$$

Where $X_1(k)$ is FFT of $X(k)$ of odd part and $X_2(k)$ is FFT of $X(k)$ of even part. $X(k)$ is FFT of first half of signal and $X(N/2 + k)$ is FFT of last half of signal. The time domain of signal and the frequency domain of signal can both help us extract the feature which can recognize the defective ceramic products.

2.4. SVM and BPNN classification methods

2.4.1 SVM

Support vector machine (SVM) is a binary classification model. The core idea is to find a hyperplane (or hypersurface) in the feature space in the training stage, which can divide the data according to different label variables as much as possible, so that the data samples which marked as 1 and which marked as 0 are on both sides of the hyperplane to the greatest extent, so as to achieve the purpose of data classification. If the dataset is divided by hyperplane, this hyperplane is called linear SVM. If the dataset is divided by hypersurface, this hypersurface is called non-linear SVM.
In an army of cases, dataset can not be divided by hyperplane. In order to simplify the solution of hyperplane, it can be mapped from low dimension space to high dimension space, but it need a large amount of computation. It can be simplified by kernel function, the definition of kernel function is as equation (4):

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$$  \hspace{1cm} (4)

The often used kernel functions includes polynomial, RBF and sigmoid(If kernel function is linear, it is linear SVM.)

3. Experimental Results

3.1. Feature parameter for ceramic products test

Then the evaluation criteria will be established by using FFT analysis tapping sound signal and explore the feature parameter which can recognize the signal by tapping defective one or the signal by tapping defectless one. Here shown two figures of signals, one is defective ceramic product another is defectless ceramic product as Figure 2(a)、 Figure 2(b):

![Figure 2. Time waveform of signal and frequency waveform of signal by tapping (a) defective ceramic product and (b) defectless ceramic product](image)

From Figure 2, it can be concluded that by tapping defective ceramic product, the sample length of signal is shorter, while by tapping defectless ceramic product, the sample length of signal is longer. Similarly, the peak of spectrum of signal by tapping defective ceramic product is lower, and this signal contains more frequency components, while the peak of spectrum of signal by tapping defectless ceramic product is higher, and this signal contains less frequency components.

3.2. SVM classifiers

In this subsection, the classify results of SVM classifiers with different kernel function will be discussed. The dataset is divided into training dataset and testing dataset by the ratio of 3:1. For each SVM classifier, penalty coefficient $C$ will be searched in the range of 0.1-1.5, the interval is 0.1, to find the parameter for each SVM classifier which make the classifier reach the highest performance in the search range, the kernel parameter $\gamma$ is default. The optimal value will be chosen according to the performance of testing dataset.

Figure 3 provide the accuracy curve of accuracy of each SVM classifier changed with C, where the $\gamma$ of each SVM classifier is certain.
Figure 3. Classification performance curves of (a) linear SVM, (b) polynomial SVM, (c) sigmoid SVM, (d) RBF SVM with different penalty coefficients

It can be concluded that the best penalty coefficient $C$ of linear SVM is 0.5, and the best penalty coefficient $C$ of polynomial SVM is 1. Sigmoid SVM possesses a terrible performance, so Sigmoid SVM is not suitable to classify. RBF SVM occurs serious overfitting phenomenon. Then $\gamma$ will be optimized to improve the performance of RBF SVM.

From Figure 3(d), when $C$ is equal to 0.6 or over 0.6, the performance of model is best. Therefore, $C$ will be set as 0.6, $\gamma$ will be changed from the range of $10^{-10}$ to 1, the interval is their exponential interval 1, that is $10^{-10}, 10^{-9}, 10^{-8}, ...$ and 1. Then Figure 4 shown the curves of performance of RBF SVM changed with $\gamma$.

From Figure 4, it can be concluded that the performance of RBF SVM in training dataset increased with the increase of $\gamma$. However, the performance of RBF SVM is increasing when $\gamma<10^6$, the performance of RBF SVM decreased when $\gamma>10^6$. Therefore, the best $\gamma$, when $C$ is 0.6, of the RBF SVM is $10^6$.

In order to comparison with SVM model, BPNN is used to establish classification model and to test the performance of BPNN classifier. The ratio of training dataset and testing dataset is also 3:1. The structure of BPNN is listed as follows:

1. In input layer, the number of neuron is 2 (not include bias, the following is same)
2. In hidden layer, the number of neuron is 4

The result of BPNN classifier, Linear SVM classifier and Polynomial SVM classifier are shown as Table 2. The results show that even though BPNN in training dataset have better performance than linear SVM and polynomial SVM, The Linear SVM and Polynomial SVM perform better than BPNN in testing dataset. In conclusion, the performance of Linear SVM and Polynomial SVM are both reaches the highest, Table 1 provide the performance of each SVM model.
Table 1. Comparison of Linear SVM, Polynomial SVM and BPNN

| Model          | Train Accuracy | Test Accuracy |
|----------------|---------------|---------------|
| Linear SVM     | 94.23%        | 96.29%        |
| Polynomial SVM | 94.23%        | 96.29%        |
| RBF SVM        | 96.29%        | 93.82%        |
| Sigmoid SVM    | 51.23%        | 46.29%        |
| BPNN           | 95.88%        | 93.21%        |

4. Conclusion
In the present study, in order to solve the problem of high cost and low efficiency in ceramic nondestructive testing, the feature parameters include sample length and peak of spectrum are used to establish SVM classifier to complete feature recognition of tapping sound signal for the target of efficient nondestructive of ceramic products detection. Then the performance of four SVMs with different kernel function and the performance of BPNN are discussed. The results prove that the SVM classifier is an efficient classifier and performed better than BPNN.

Limited by the experimental conditions, this study only focused on detecting whether the ceramic products have defects. The method of distinguishing the defect type of ceramic products is worthwhile to be researched in the future work.

Acknowledgments
This work is supported in part by the Hebei Provincial Science and technology plan under grant 20327218D, and the Graduate innovation project of North China University of Technology under grant 2019B28.

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