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Nondestructive characterization and artificial intelligence recognition of acoustic identifiers of ancient ceramics

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Abstract

Cultural heritage identity management is the most basic and important work in the process of cultural heritage protection. It is of great significance to provide a unique and identifiable digital identity for ancient ceramics. At present, the identification information of ancient ceramics is mainly composed of external visual characteristics, and there is no report on feature identification method that can reflect the properties of ancient ceramics. Audible sound signals not only have advantages in non-destructive testing, but also can be used as voiceprint information to identify, monitor and analyze ancient ceramics. In this paper, seven ancient ceramics and 12 similar modern ceramic cups are taken as research objects, and an acoustic identifier (AID) is constructed. We put forward a reliable acoustic identification method for ancient ceramics, and established a digital code of acoustic characteristics of ancient ceramics. The results show that audible sound waves can reflect the attribute information of ancient ceramics. Sufficient acoustic data combined with deep learning can not only accurately match the identity of ancient ceramics, but also detect the real-time identity information of ancient ceramics, and make a comparative analysis of its cracks and whether it has caused damage. This method can provide a variety of practical applications for audible signal feature recognition technology in the exhibition, protection, trading, recognition and safety management of ancient ceramics and other cultural relics.

Keywords Ancient ceramics, Acoustic identifier, Non-destructive testing, Deep learning, Heritage management

Introduction

The identification and management of cultural relics can be more efficient and accurate through the unique identification code of cultural relics [1, 2]. At present, the identification of cultural relics is mainly in the form of their name, category, number and descriptive information. The identification information of cultural relics mainly consists of external visual features such as 2D images and 3D scanning data [3, 4]. For imitations of the same size and extremely similar appearance, the characteristic information of the above-mentioned data is limited and cannot be the only indicator to identify the identity characteristics of cultural relics. Cultural relics should be endowed with unique digital identifiers and identification information. Therefore, it is necessary to conduct more comprehensive and in-depth research on the calibration,

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recording and nondestructive identification of cultural relics [5].

Sound signal is rich in information, which not only has unique advantages in nondestructive testing, but also can be used as voiceprint information for identification, monitoring and analysis [6, 7]. The audible sound has been widely used in nondestructive testing, such as wood, mechanical parts, steel bars, food quality testing and so on [8–10]. The speed of sound propagation will also change with the structure and density of the object. The properties or defects of objects can be analyzed according to the sound characteristics of solid sound transmission [11]. In addition, the acoustic behavior of an object can be predicted preliminary according to its natural frequency, which is related to its composition, structure, mass, and size [12–14].

The raw materials of ancient ceramics are basically from the place of origin, and the firing methods of different kilns have their own characteristics [15, 16]. In the case of ancient ceramics, it is necessary to identify the information reflecting its own attributes. In this study, the acoustic characteristics of ancient ceramics were analyzed to establish stable and reliable acoustic identifiers (AID), which is the vibration spectrum information of a solid after sound transmission through ancient ceramics. The AID of ancient ceramics reflects the inherent characteristics of their material and structural state.

Deep learning is a core technology in the development of artificial intelligence, which has achieved optimal and even surpassed human results in research fields of voice classification, voice recognition and voice processing [17]. Deep learning is a branch of machine learning. Deep learning can automatically learn features, while traditional machine learning requires manual feature calibration to extract features [18]. Deep learning can automatically learn complex data features through multi-layer mapping of neural network, which reduces the workload of feature engineering and relies less on original data [19]. In this paper, a nondestructive detection and identification system for ancient ceramics is designed. Researchers can conduct nondestructive testing on ancient ceramics and record their AID at that time for further study. At the same time, the measured acoustic waves of ancient ceramics are recorded into the database as their AID, and the artificial intelligence platform is used to establish sound classification models for the deep learning of these acoustic data. Through these recorded acoustic data, the integrity of the cultural relics in the future can be compared, analyzed, and identified as to whether they are newly damaged, repaired or replaced. Therefore, the identity and status of cultural relics can be accurately identified and further traced. It is of great significance to the collection, management, deterioration analysis, authenticity identification and analytic cognition of cultural relics.

Methods

The purposes of this study are as follows: (1) design acoustic measurement methods and devices suitable for ancient ceramics; (2) construct AID that can represent the identity and state of ancient ceramics; (3) customize the classification model and result characterization method of ancient ceramic AID recognized by artificial intelligence.

Samples

As shown in Fig. 1a, seven ancient ceramics of different types and sizes are taken as research objects, including two blue and white porcelain plates, two blue and white porcelain bowls, two celadon jars and one celadon bowl. The samples were provided by the key laboratory of materials and technology for underground cultural relics protection, Ministry of education, Shaanxi University of Science and Technology, and their basic information was shown in Table 1.

Figure 1b shows 12 ceramic cups produced in the same batch, which use the same raw materials, forming process and firing system. The only difference between them is that their cups are printed with different designs of the Chinese zodiac, including rat, ox, tiger, rabbit, dragon, snake, horse, goat, monkey, rooster, dog, and pig.

Experimental method

The acoustic analysis system of ancient ceramics based on artificial intelligence technology is composed of two parts: acoustic parameter acquisition device and artificial intelligence analysis platform (Fig. 2). The first part is the acoustic parameter acquisition device, including audio power amplifier (AV-699BT, China), vibration pickup device (Korg, CM-300, Japan), dual microphone preamplifier (M-Audio, Audio buddy, USA) and computer. The audio vibrator is a kind of piezoelectric microphones, which can play audible sounds ranging from 20 Hz to 20 kHz. According to the shape and size of the ancient ceramics, choose appropriate pickups, such as patch pickups, pickups clip, piezoelectric sensing film, etc. The pickup device selected in this study is a pickup clip. The pickups can only receive the vibration transmitted by ancient ceramic structures, not air-borne vibration. When the ancient ceramic vibrates, the magnetic induction lines will be cut in the magnetic field inside the pickup, and the coil around the magnetic core will generate induced current, so the pickup can convert the vibration signals collected from the ancient ceramics into electrical signals without interference from other vibration waves from the air medium.

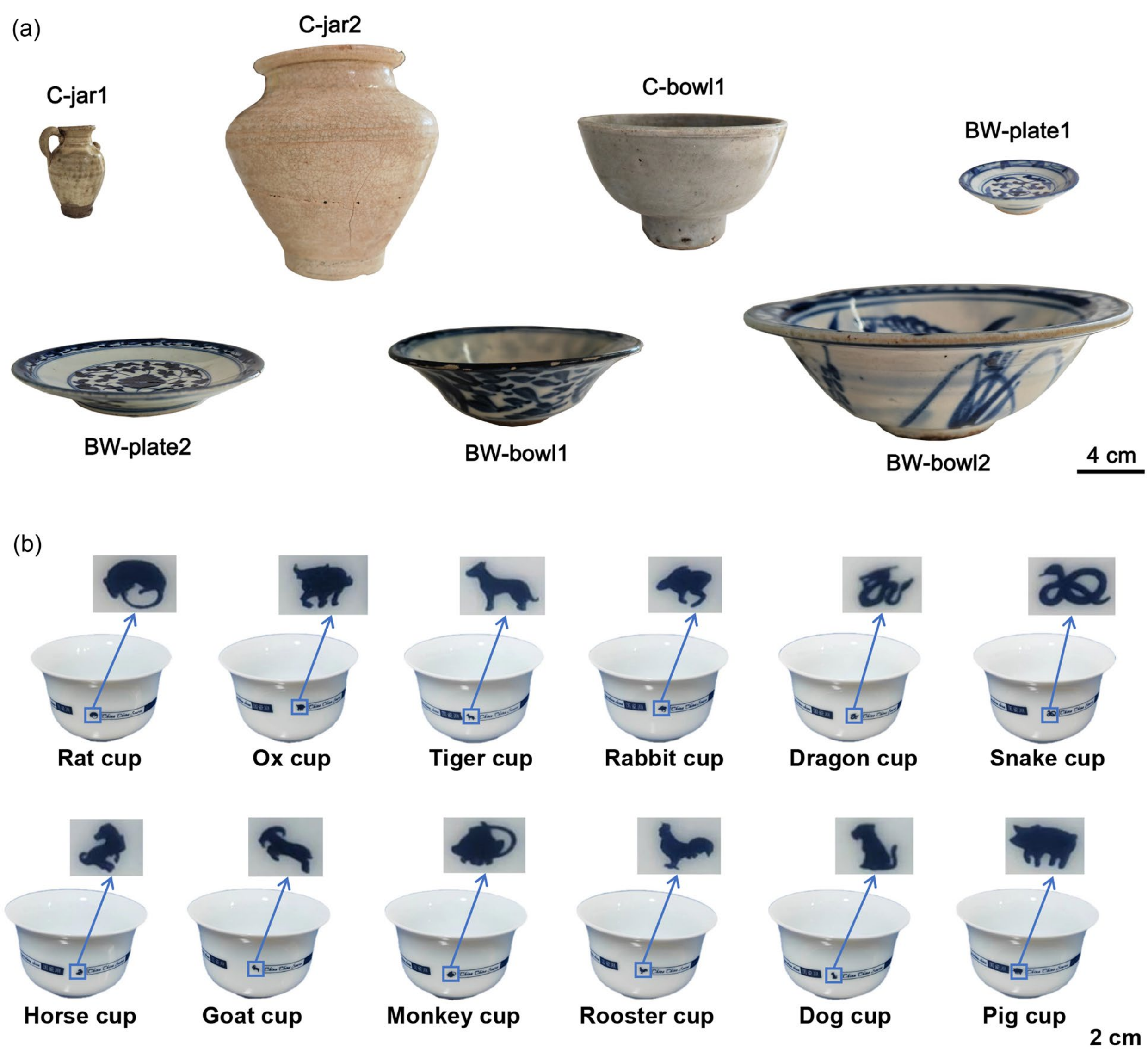

Fig. 1 Ceramics samples; **a** seven ancient ceramics samples; **b** 12 Chinese zodiac modern ceramic cup samples

Table 1 Basic information of ancient ceramic samples

Sample number	Dynasty	Category	Shape
C-jar1	Tang (618–970 AD)	Celadon	Jar
C-jar2	Ming (1368–1644 AD)	Celadon	Jar
C-bowl1	Qing (1636–1912 AD)	Celadon	Bowl
BW-plate1	Qing (1636–1912 AD)	Blue and white porcelain	Plate
BW-plate2	Qing (1636–1912 AD)	Blue and white porcelain	Plate
BW-bowl1	Qing (1636–1912 AD)	Blue and white porcelain	Bowl
BW-bowl2	Qing (1636–1912 AD)	Blue and white porcelain	Bowl

After measuring the acoustic signals of the ancient ceramics, the acquired acoustic signals are converted into digital signals using a dual microphone preamplifier, and the data is recorded and analyzed using computer software. The sound is then deeply learned and recognized using Easy DL, an open-source platform for artificial intelligence. Easy DL supports customized model training and supports a full range of functions in model development [20]. Easy DL platform is built on the PaddlePaddle framework, which consists of multi-machine parallel architecture, multi-GPU parallel architecture, sequence model and large-scale sparse training, which is suitable for this study. PaddleBook and the available

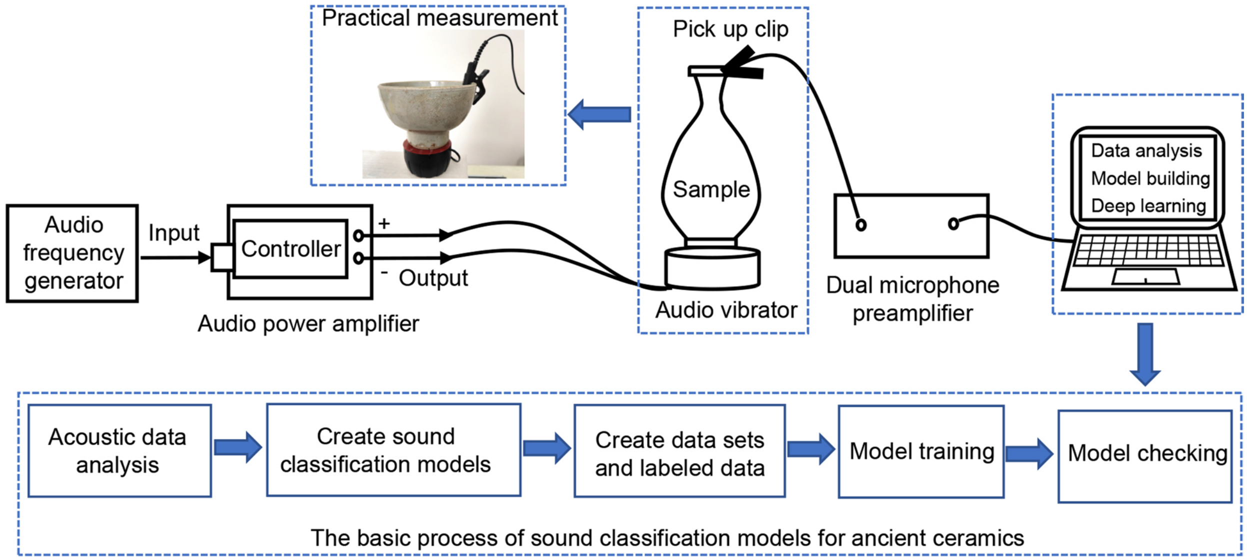

Fig. 2 Acoustic parameter measuring device and the process diagram of the vibration classification model for ancient ceramics

online validation model set PaddleModels also add some knowledge of deep learning, which makes PaddlePaddle the reason for choosing the deep learning framework [21–23]. The basic flow of the acoustic classification model is shown in Fig. 2. Once a predetermined amount of data has been measured, a customized acoustic classification model for ancient ceramics can be obtained through the functions of data set management, model training, model evaluation, model verification and model publishing.

Results and discussion

Acoustic signals of ceramic samples

The acoustic parameters of seven ancient ceramic samples were measured with a sinusoidal variable frequency generator of 20 Hz to 20 kHz. As shown in Fig. 3, it is the audio signal result of generator, and results of the signal passing through seven samples respectively. The duration of this sine wave sweep signal is 10 s. The sampling frequency is 44,100 Hz, and the frequency resolution is 0.1 Hz. Within the range of 2 s to 6 s, the pickup receives strong vibration transmitted by ancient ceramic structures. When the amplitude of the measured vibration transmitted by ancient ceramic structures was greater than 0.5 dB, there will be a slight displacement in the experiment of the ancient ceramic sample, which is the resonance phenomenon. In the resonance process, the sample will produce violent vibration and knock the generator. At this time, the level signal obtained by the pickup clip exceeds 100%, and the measured time-domain signal will be saturated. The saturation of the signal in Fig. 3 means these ancient ceramic samples were resonated. As shown in Fig. 3, it has been found that ancient ceramic samples may have resonance between about 200 Hz and 900 Hz. Resonance is the phenomenon of a surge of energy in the whole system when the external excitation frequency of the system is equal to some specific value, and these specific external excitation frequencies are the natural frequencies of the system [24, 25]. As shown in Fig. 3, it was found that the resonance did not occur at a single frequency, but in the resonance band from about 200 Hz to 900 Hz.

According to our previous research, the mass and elastic modulus of ancient ceramics are the two main factors that affect the resonant frequency of ancient ceramics. When the material properties (density, Poisson's ratio, etc.) of ancient ceramics are different or the shape is different, the affected parameters are still mass and elastic modulus [26, 27]. When the boundary conditions of a structure are different, the natural frequencies must inevitably be different, because the boundary conditions will affect the distribution of elastic modulus of the structure. Meanwhile, the elastic modulus of ceramics is related to the phase type, particle size, distribution, proportion, and porosity of ceramics [28, 29].

Deep learning and recognition of ancient ceramic AID

For the detection and identification information collection of precious cultural relics such as ancient ceramics, the most basic premise is to ensure the safety of cultural relics. Ancient ceramics are brittle and may be damaged or potentially damaged if the test signal causes them to resonate. Therefore, in the subsequent detection, we chose to avoid the resonance frequency band

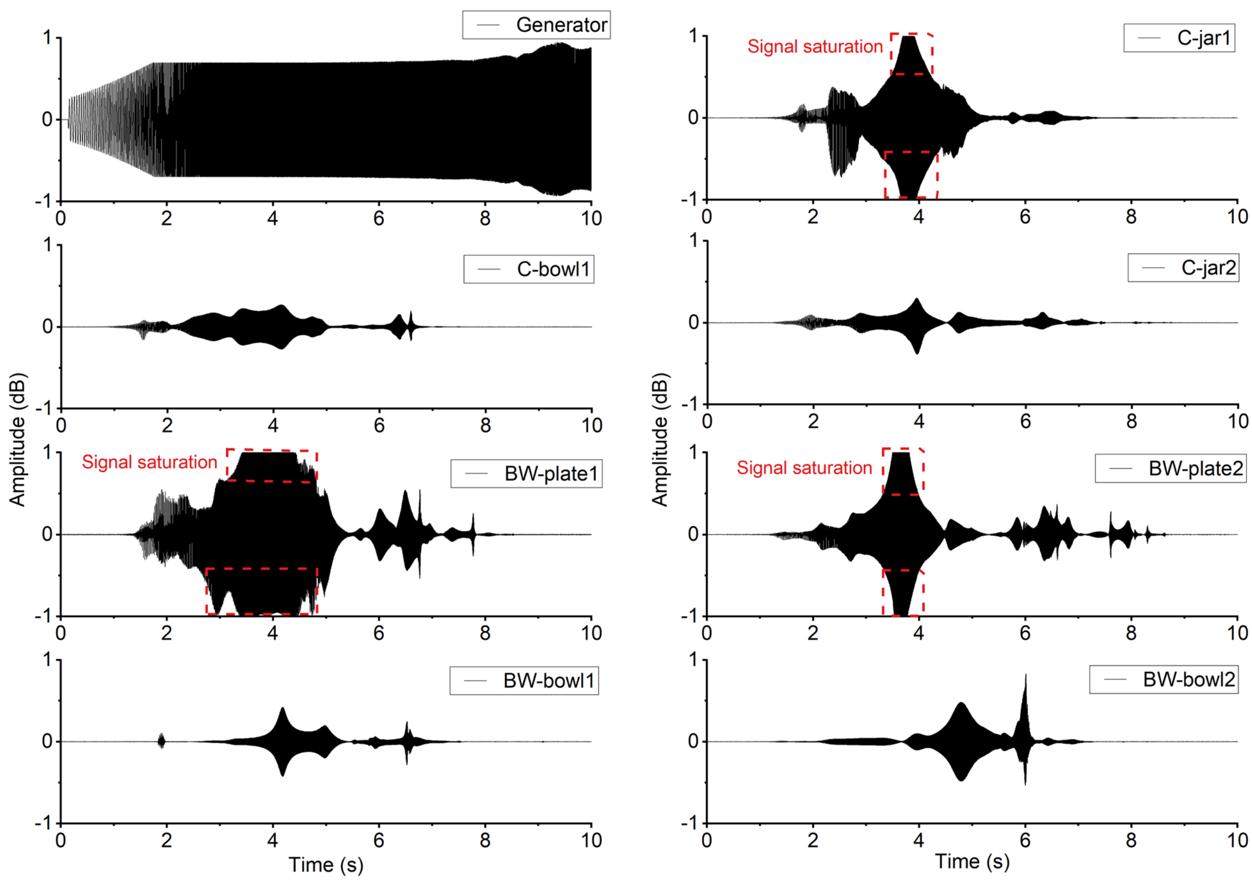

Fig. 3 The time domain curves of the generator and the vibrations transmitted by ancient ceramic structures at 20 Hz to 20 kHz

of the samples, and chose the non-resonance frequency 1000 Hz, which is relatively close to the resonance frequency band, as the generator frequency. This sound wave can reflect the state parameters of the sample, such as small differences due to cracks, pores and attachments in the sample [30]. This is to ensure the stability of the test data, and it is more important to avoid any possible damage to ancient ceramics caused by resonance. The sampling frequency is 44,100 Hz. Each sample was tested 50 times, each test lasted for 4 s, and a single test collected about 176,400 data sampling points. These acoustic data points make up the AID of ancient ceramics.

As shown in Fig. 4a, it is the 1 kHz audio generator and the time-domain signals of seven samples. The intensity of the acoustic amplitude of each sample is different. Each sample has different sound loss. The mass of the sample and the propagation path of the signal are the main factors affecting the sound loss. Mass is the product of density and volume, the greater the mass of the sample, the more the diffusion attenuation of sound waves. The longer and more complex the propagation path of sound wave in ceramic, the greater the heat loss of sound wave in ceramic. In addition, cracks and materials in ancient ceramics will also affect the measured path of sound wave propagation. It is these factors that constitute the unique acoustic identity of each ancient ceramic.

In addition, the frequency domain characteristics of samples can be seen after Fourier transform of the time domain signal, as shown in Fig. 4b. The sampling frequency is 44,100 Hz, and the frequency resolution is 0.1 Hz. In order to make the characteristics of the curve in the frequency domain more obvious, we smoothed the curve with a smoothing index of 1/96. It can be found that the main frequency 1 kHz amplitude of each sample is different. In addition, there are a lot of harmonics in the frequency domain of each sample, and the distribution and amplitude of these harmonics are also different. These characteristics constitute the characteristic information of each ancient ceramic AID.

We uploaded 350 audio data into the ancient ceramic sound classification model created on Easy DL, label the data, and then train the model. In the model training, the system carries out deep learning on the 350 audio data. After deep learning, 105 audio data was

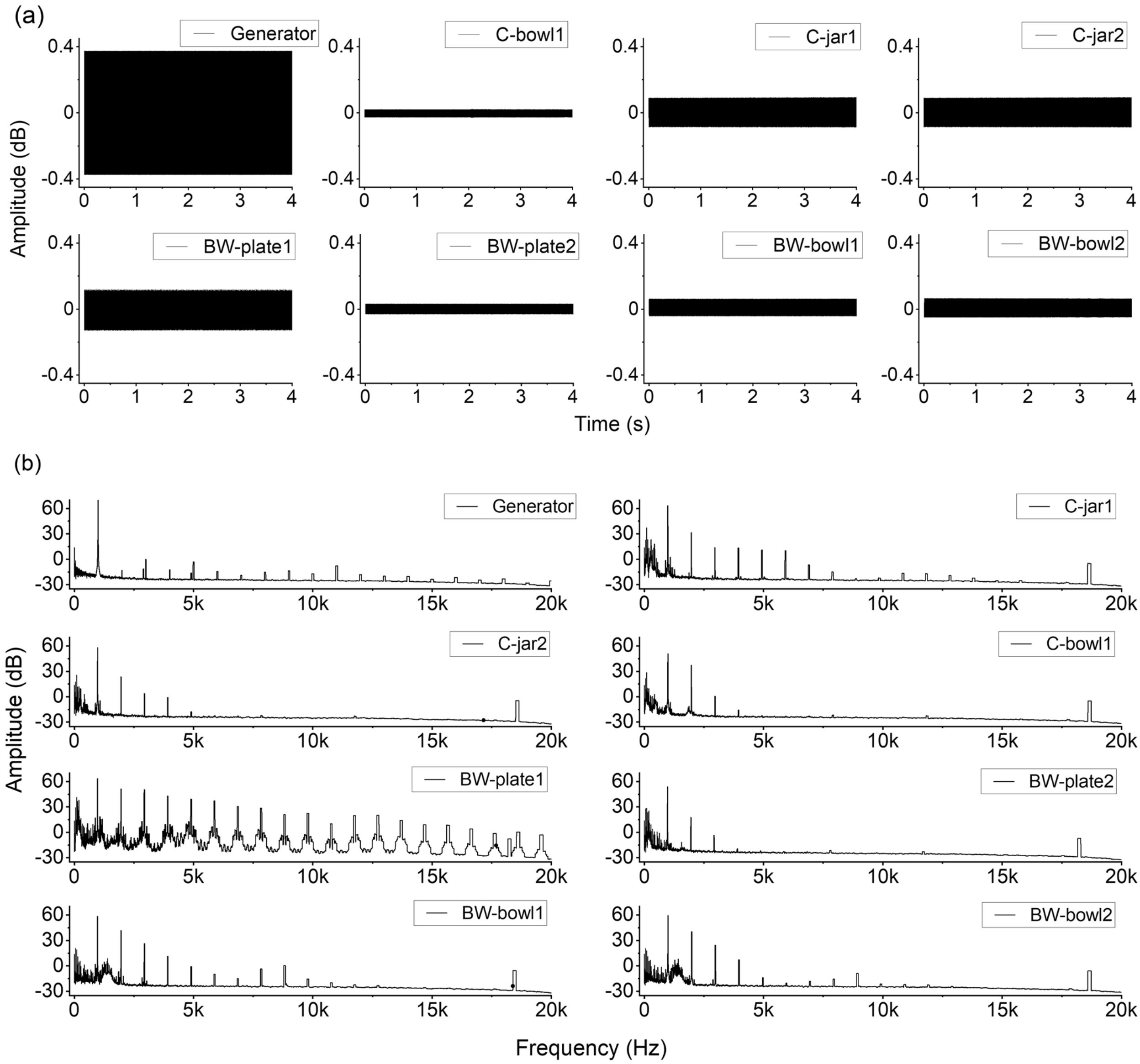

Fig. 4 Acoustic parameters characterization of ancient ceramic samples at 1 kHz; **a** time domain curves of generator and ancient ceramic samples; **b** frequency domain curves of generator and ancient ceramic samples

randomly predicted by the random test set of the model. The number of correctly predicted performance was 103, the number of incorrectly predicted performance was two, and the accuracy rate of the model was 98.1%. Therefore, we increased the number of test data for a single sample from 50 to 100 times, and the total number of data reached 700. The model randomly predicted 210 audio data again, and the accuracy of the model increased to 100%. When the amount of data in the model is larger and the data features are more stable, the recognition accuracy of the model will be higher.

Then, we measure these seven samples twice again, and put the measured data into the trained model for verification. The verification results were shown in Table 2. The recognition accuracy rate of all samples is 100%, and the recognition matching degree is 96.24% to 100%. In order to explain the reasons for the fluctuation of recognition results, we take the test results of sample BW-bowl 2 as an example for analysis. As shown in Fig. 5a, the BW-bowl 2 sample has some cracks near the measurement point, and the position of the pickup clip is held along the direction of the cracks. In the data acquisition process of Result 1, the position of the

Table 2 Audio recognition results for seven ancient ceramic samples

Sample Number	Result 1	Recognition rate (%)	Result 2	Recognition rate (%)
C-bowl1	C-bowl1	99.97	C-bowl1	99.94
C-jar1	C-jar1	99.99	C-jar1	100
C-jar2	C-jar2	97.05	C-jar2	99.99
BW-plate 1	BW-plate 1	99.99	BW-plate 1	100
BW-plate2	BW-plate2	98.69	BW-plate2	100
BW-bowl1	BW-bowl1	100	BW-bowl1	96.24
BW-bowl2	BW-bowl2	99.84	BW-bowl2	99.40

pickup clip is the same position and direction. However, when data was collected for Result 2, the position and direction of the pickup clip was changed, and it crossed the crack.

As shown in Fig. 5b and c, when the measurement direction changes, the contact position between them will deviate, and the signals picked up in the time domain and frequency domain will be significantly different. It can be clearly seen from the frequency domain waveform that the amplitudes of some characteristic peaks have changed, but the position of the characteristic peaks has not changed obviously. This leads to the change in the matching rate of the recognition, but it does not lead to recognition error. This can be improved by keeping the consistency of measurement points during the test. At the same time, when the amount of deep learning data increases, the recognition accuracy will also be improved in this case.

Deep learning and recognition of modern ceramic samples

We use the laser positioning sensor (ZW-LV100R-NP, China) to make bidirectional positioning measurement

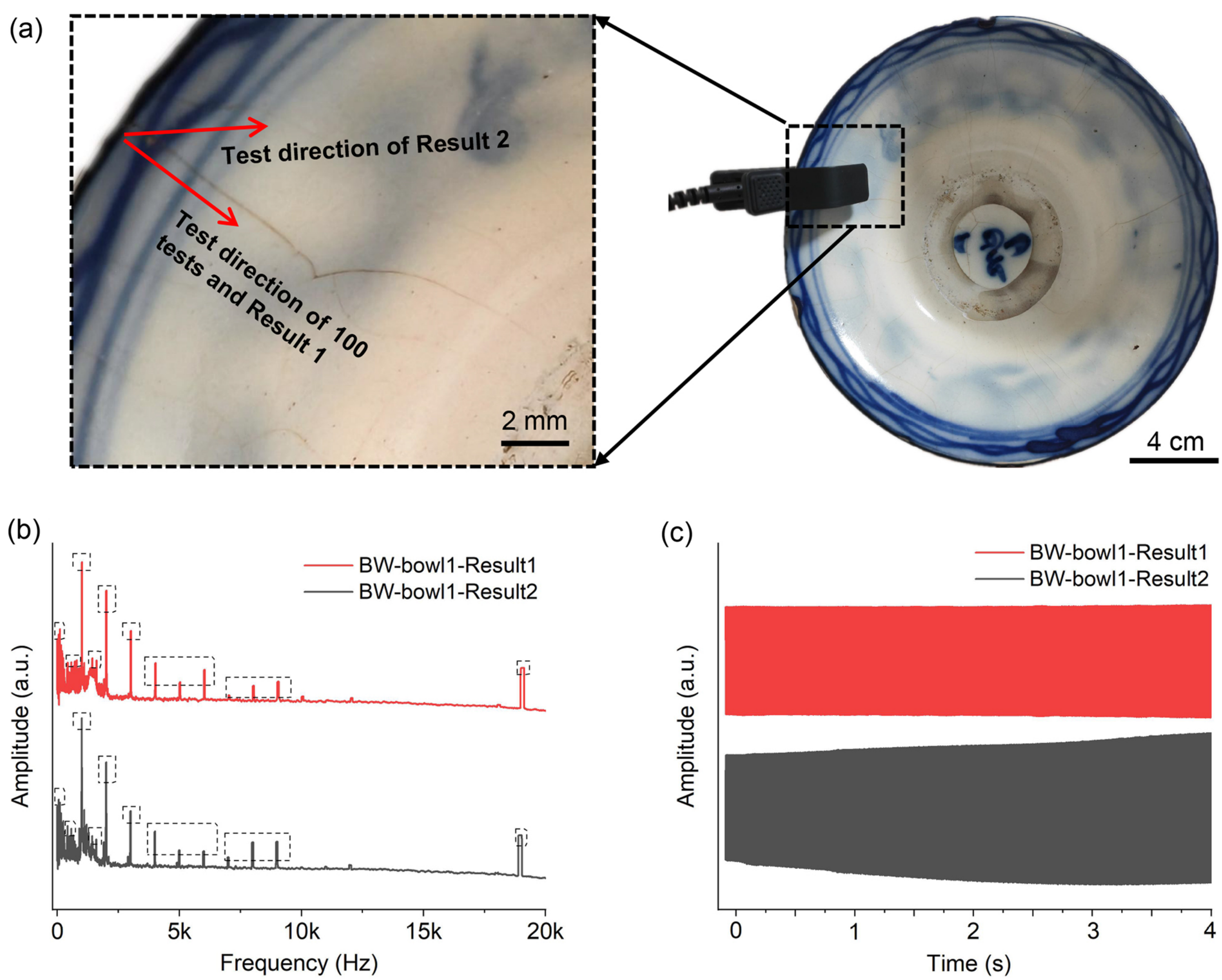

Fig. 5 Analysis of influencing factors of acoustic parameters of sample BW-bowl 1; **a** photos of measuring position of BW-bowl 1; **b** frequency domain curves of BW-bowl 1 twice test data; **c** time-domain curves of BW-bowl 1 twice test data

on the sample, to avoid the inaccurate identification accuracy due to the inaccurate location of the collection point, as shown in Fig. 6a. It can make sure the collection points are in the same position at each measurement. The reflective film at the laser positioning point was shown in Fig. 6b. The reflective film can reflect the laser light to the positioning sensor, so that the sensor can determine the position of the sample, as shown in Fig. 6c and d. We collected the information of the same test point on the sample for three times by using 1 kHz sine wave audio with a duration of 4 s, and it was necessary to reposition the sample and reposition the pickup clip each time. It was found that the acoustic data measured by this method had the same characteristics, as shown in Fig. 6e. This shows that the laser positioning method may reduce the measurement error and improve the accuracy of recognition. To further confirm the results, vibration signals were collected from 12 samples.

Consistent with the measurement of ancient ceramic samples, 1 kHz was chosen as the generator frequency. The sampling frequency is 44,100 Hz. Each sample was only tested 20 times, each test lasted for 4 s, and a single test collected about 176,400 data sampling points. Acoustic parameters of 12 Chinese Zodiac modern ceramic cup samples at 1 kHz as shown in Fig. 7. As shown in Fig. 7a and b, even 12 ceramic cups produced from the same batch, with the same composition, manufacturing method and firing method, have different vibrations transmitted through the samples. Acoustic parameters can show the structural differences between them, showing their unique "voiceprint information." Among them, the time domain signal of the Dog-cup is significantly higher than that of other cups. It is found that there is a crack at the bottom of the Dog-cup, which will cause the sound wave cross-section to reflect, resulting in an increase in the amplitude of the time domain frequency.

At the same time, we found that after laser localization of the samples, even though the modern ceramic samples are very similar, and the number of measurements is reduced to 20 times compared with the ancient ceramic samples of 50 times, the success rate of recognition and similarity rate are 100%. This shows that if the location of the measuring point is consistent, the identification information of ancient ceramics at this measuring point can be repeatedly obtained, so as to realize the identification of ceramics with high precision.

Conclusions

This study proposed an AID for ancient ceramics based on acoustic vibration spectra, and designed an acoustic analysis system for ancient ceramics, which is composed of acoustic parameter acquisition device and artificial intelligence analysis platform. The acoustic parameter acquisition device enables non-destructive measurement and stable recording of acoustic parameters of ancient ceramics of various sizes and vessel types. The

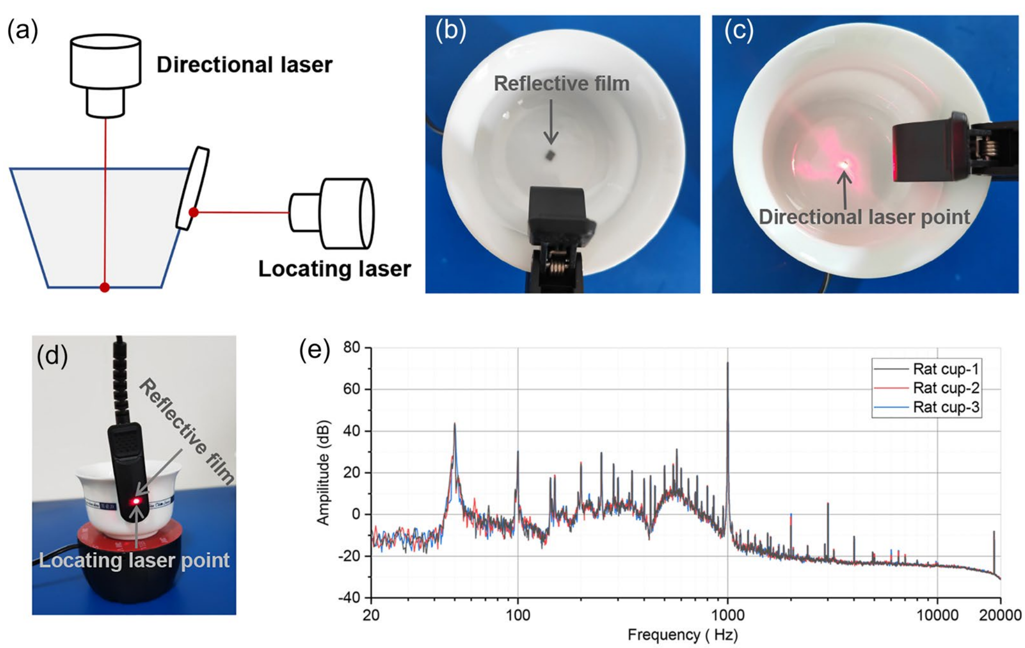

Fig. 6 Ceramics measuring point positioning measuring device and schematic diagram; **a** schematic diagram of positioning laser and directional laser; **b** reflective film at the location of the directional laser point; **c** directional laser and reflective film at positioning point; **d** positioning laser and reflective film at measuring point; **e** frequency domain curves of the ceramic cup sample were measured three times

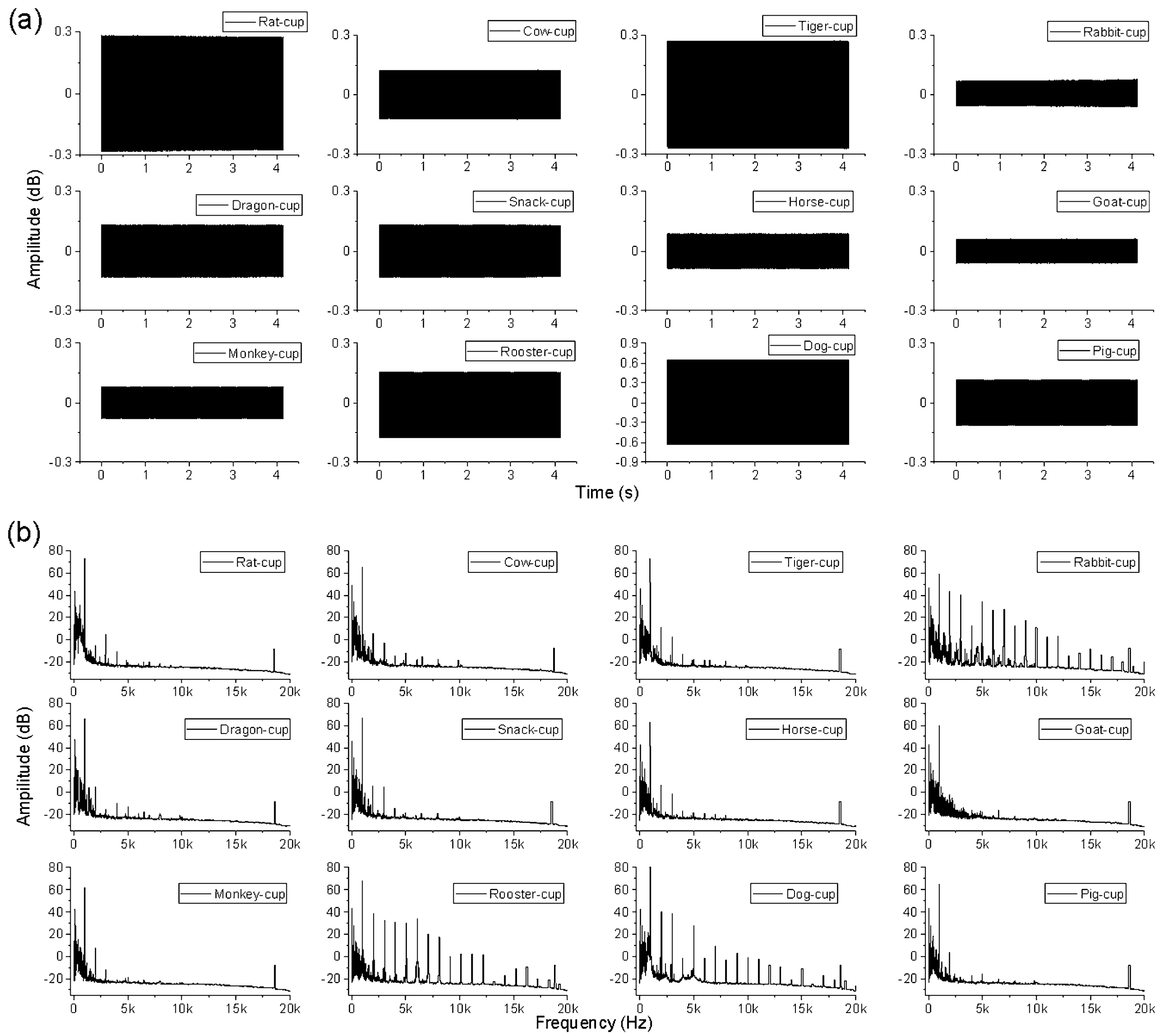

Fig. 7 Acoustic parameters characterization of 12 Chinese zodiac modern ceramic cup samples at 1 kHz; **a** time domain curves; **b** frequency domain curves

AID of ancient ceramics reflects the vibration spectrum characteristics of ceramics, which is closely related to the material and structural state of ancient ceramics and records the comprehensive performance characteristics of ancient ceramics.

Through the acoustic classification model of ancient ceramics, the deep learning of AID is carried out to realize the non-destructive, accurate and fast recognition of ancient ceramic AID by artificial intelligence. When the number of data tests of a sample reaches 100, the recognition accuracy of all samples is 100% and the recognition matching degree is 96.24% to 100%. Through the laser positioning of 12 Chinese zodiac modern ceramic cups, it is found that the recognition accuracy can reach 100%. The recognition and matching degree can be further improved by increasing the amount of measurement data and the clamping accuracy of device. It is possible to establish and publish API at a later stage to complete the application of the AID database and intelligent identification program.

By deeply learning the acoustic transmission parameters of ancient ceramics and comparing the sound information of solid acoustic transmission of ceramics with PaddlePaddle platform, it can accurately identify whether ceramic samples are replaced, repaired or damaged. This is of innovative significance for the establishment of digital coding of cultural relics, and has important applications for the collection, management, deterioration analysis, authenticity identification, analysis, and cognition of cultural relics.

Abbreviations

2D	Two-dimensional
3D	Three-dimensional
AID	Acoustic identifiers
API	Application programming interface

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Author contributions
XJ: Investigation; software; data curation; visualization and writing-original draft. XW: Conceptualization; methodology; supervision and writing—review. CX: Supervision and formal analysis.

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Availability of data and materials
The data are not publicly available due to their containing information that could compromise the privacy of the National Key Research and Development Program of China (Grant No. 2019YFC1520100 and 2019YFC1520200).

Declarations

Competing interests
The authors declare no conflict of interest.

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