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Seismic Signal Adaptive Endpoint Detection Based on Human-Computer Interaction

Yue Wang*

Hebei Agricultural University, Baoding, China

**corresponding author*

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Abstract: With the development of artificial intelligence technology, robot technology has become more mature, and human-computer interaction technology has become more widely used. China is a country with frequent earthquakes. The application of robot technology to seismic signal detection is of great significance to solve various problems in earthquake disasters. The research purpose of this paper is to study adaptive endpoint detection of seismic signals based on human-computer interaction technology. Based on the analysis of adaptive noise reduction of signal autocorrelation function, this paper references the concept of autocorrelation similarity distance, and proposes human-machine interaction technology Seismic signal adaptive endpoint detection, discusses the description of noise and noisy signals based on autocorrelation similarity distance, and summarizes the adaptive endpoint detection method of seismic signals based on human-computer interaction technology, and gives the specific implementation of the algorithm Compared with the experimental detection results obtained by this method and the time-domain waveform envelope and the method of manually detecting the time-table seismic signal endpoint detection, the research results in this paper show that the accuracy of this algorithm is as high as 96.11%, Under the condition of noise ratio, the end position of the seismic signal can still be detected more accurately by using this algorithm.

1. Introduction

With the development of science and technology, robots have been widely used in high-tech industries such as equipment manufacturing, new materials, biomedicine, and intelligent new energy. The integration and development of robots with artificial intelligence technology, advanced manufacturing technology, and mobile Internet technology has promoted changes in human social lifestyles. At present, the Chinese robot market has entered a period of rapid growth and has obvious advantages in some fields. With the rapid development of robot technology, robots have been widely used in various fields. It is of great practical significance to study robots that can replace humans in the disaster scene environment.

The development of robotics has brought many conveniences to people's lives and work. With the continuous development and wide application of computer technology, wireless communication technology and mobile computing technology, the problem of human-computer interaction under various vibration conditions is increasingly prominent, and robot technology has been widely used [1-2]. In the research of seismic event detection, location and identification, the precise determination of signal endpoints is of great significance. The endpoints of the signal mainly include the initial motion and starting and ending points of the P wave group, S wave group, and surface wave group. After these endpoints are accurately detected, the time difference and propagation time of the seismic signals of each wave group sent to the seismic station can be calculated [3-4]. Based on the known P-wave, S-wave, and surface-wave propagation velocities, the source location can be calculated more accurately, and the suspicious nature of the nuclear explosion of this earthquake can be determined initially based on the sensitivity of the source location, and the preliminary screening of this earthquake is completed. On the other hand, according to seismic principles, the initial motion polarity of natural seismic signals can be negative, and the initial motion polarity of nuclear explosion seismic signals should always be positive. Therefore, after precisely locating the initial motion, the source attributes can also be identified [5-6]. Although seismic signal endpoints are of great significance for the screening and identification of events, for a long time, endpoint location has been mainly based on time-domain waveform envelopes and manual lookup of timetable seismic signal endpoint detection methods, that is, manual detection, which is prone to misjudgment. There are also certain errors in leak detection. Therefore, it is important to find a high-precision adaptive seismic signal endpoint detection method.

Guillermo Cortés, M. has proposed a dual-threshold microseismic signal detection method based on constraint judgment. Guillermo Cortés, M used constraint judgments to quantitatively analyze the improvement effect of false alarm probability and its effect on detection probability. Guillermo Cortés, M. once established a mathematical model based on constraint judgment for double threshold detection of total PFA and PD, and verified the validity of the mathematical model through simulation experiments and experiments. The research results of Guillermo Cortés, M show that the introduction of constraint judgment in double threshold detection reduces the signal-to-noise ratio under timing PFA and PD calls and improves the recognition accuracy of microseismic signals. Although Guillermo Cortés, M's method improves the recognition accuracy, the stability of this method is not high, and it needs to be improved in practical applications [7-8]. Natural gas hydrates are buried shallowly in the permafrost regions of the Hara Lake region of Qinghai. The seismic signals are often submerged by noise. The reflection signals related to formations and hydrates can be effectively separated from complex seismic waves. The regional seismic data was analyzed in detail, the types and characteristics of noise were summarized, and then the signal extraction process was proposed, including techniques such as noise attenuation, amplitude compensation, deconvolution, and superposition. It is used in prestack gathers, effectively suppresses various noises, retains reflected signals to the maximum, improves seismic resolution, signal-to-noise ratio, and fidelity of results, and is of great significance for seismic interpretation and natural gas hydrate prediction.. Roee Diamant's method has high fidelity, but its accuracy is not enough and needs to be improved [9-10]. When the signal-to-noise ratio (S / N) is less than -3db or even 0db, it is often difficult to identify seismic events from ordinary gun records. To overcome this problem, Elena Palahina proposed a method to detect weak seismic signals based on the vibrations described by phase space chaotic dynamical systems. The basic idea is that nonlinear chaotic oscillators are highly immune to noise. Such a dynamic system is less affected by noise, but is more sensitive to periodic signals. It is changed from a chaotic state to a large-scale periodic phase state under the excitation of a weak signal. In order to detect the degree of noise pollution on the signal, Elena Palahina used the oscillator controlled by the Duffing-Holmes equation to perform a numerical experiment with a distorted Ricker wavelet sequence as the input signal. Elena Palahina proved that in a strong noise environment, the oscillator system can achieve a wide range of periodic phases. In the case of ordinary artillery records with low signal-to-noise ratio, the artillery sets reflected from the same interface are similar to each other and can be placed on a single recording track with a common reference time, so the periodicity of the generated signal changes with the movement [11- 12].

This paper proposes an adaptive endpoint detection method for seismic signals based on human-computer interaction technology. This method is an endpoint detection method with similar distances of correlation coefficients. This method has no special requirements for geological knowledge and noise changes, and can be used in Under the condition of lower signal-to-noise ratio, the precise detection of adaptive endpoints is realized. Moreover, the adaptive correction method of seismic signal phase is studied, and the results of adaptive correction of vibration record phase are compared and analyzed through simulation experiments.

2. Proposed Method

2.1. Human-Computer Interaction Technology

Human-computer interaction refers to the means of mutual understanding between human and computing, including interaction methods, methods, devices and interfaces, also known as human-machine interface or human-machine communication [13-14]. The development trend of human-computer interaction reflects the constant emphasis on human factors, making the on-machine interaction closer to the natural form, enabling users to use daily natural skills without requiring special effort and learning, and reducing cognitive load. Improve work efficiency [15-16].

(1) Human-Computer Interaction in Mobile Computing

Mobile computing is different from traditional fixed and mobile computing models in many aspects such as computing concepts, human-computer relationships, interaction methods, functions, and uses [17]. Mobile computing technology has expanded the development space of on-machine interaction to a certain extent, and specific interaction tasks and interaction devices have promoted the birth of new interaction technologies. Figure 1 and Figure 2 are schematic diagrams of traditional human-computer interaction and human-computer interaction of mobile computing.

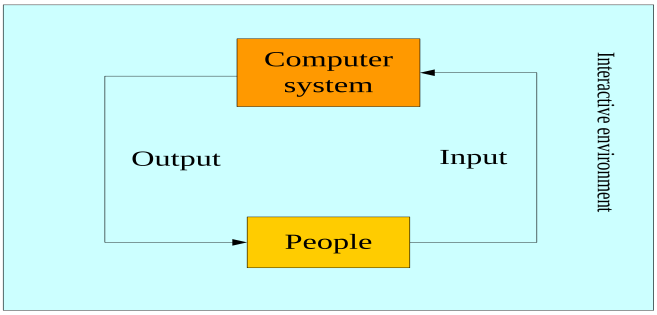

Figure 1. Traditional HCI

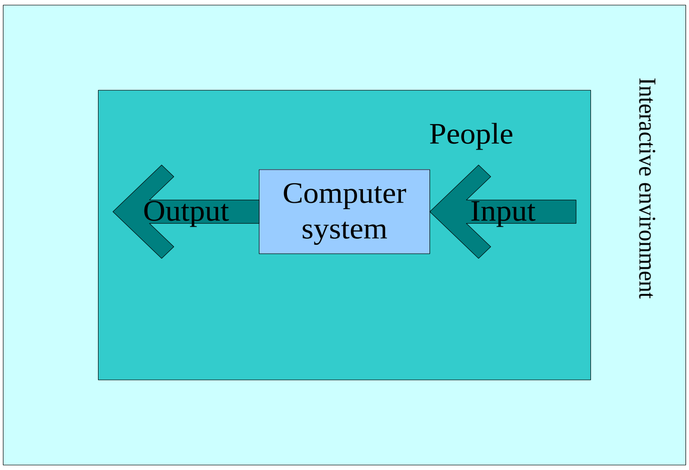

Figure 2. MHCI

As can be seen from Figure 1 and Figure 2, in traditional human-computer interaction, the computer is stationary, and people use the computer as the center to perform calculations. At the same time, the human-machine is separated. These characteristics increase the time and place of calculation. Computation of human-computer interaction is a kind of human-computer interaction in a state of motion, emphasizing human as the core, and the computer plays the role of enhancing and assisting human, that is, human-machine integration.

Mobile computing puts forward high requirements for human-computer interaction methods, but due to some bottlenecks in the research of natural interaction technologies, natural interaction methods such as speech and facial expressions cannot meet the interaction needs of mobile computing [18-19]. For researchers of mobile computing and ubiquitous computing, one of the research focuses is to try to break the traditional desktop-based computing model and make computing service devices as flexible as users [20]. To make users abandon the traditional static desktop method, we cannot force users to find and discover new ways to interact with the computer. Instead, we must provide a response to the user's location and services through the analysis of context-aware knowledge. The interactive interface enables the computer to change from a passive service mode to an active service mode, and makes the human-computer relationship more natural and harmonious [21-22].

(2) Common human-computer interaction devices

With the development of human-computer interaction technology and mobile computing technology, human-computer interaction devices have greatly improved in form and interaction [23]. Human-computer interaction devices are mainly divided into two categories according to the flow of information sent and received by humans and computers: input devices and output devices [24]. Common input devices today are mainly divided into pointing input devices and text input devices; output devices are mainly display output devices [25].

1) Pointing input device

The pointing device is still mainly a mouse, and there are Trackball, Trackpad, Trackpoint, stylus and so on in the form. The popularity of computer graphics operating systems has led to the rapid development of pointing devices. And mobile computing has played a huge role in promoting the development of pointing devices. Many new pointing devices are targeted at mobile computing platforms [26].

Mouse

The mouse is a common pointing device on a PC. The principle of the mouse is to establish a coordinate system on the screen of the display device, and the purpose of mouse movement is achieved by moving between the corresponding coordinates. There are two types of mouse: mechanical and optical. The mouse operates the computer through the left and right keys (there is also a three-button mouse, and the middle key is the scroll key).

Handle

The joystick is a mobile input device developed from video games. Its pointing operation uses the arrow keys, which is not efficient in interface operations. The handlebar has a very good performance in menu operation, and at the same time, it has outstanding performance in controlling the game. However, the input method of the handle has greatly inspired researchers. Trackpoint is a miniature "finger handle" invented based on the input method of the handle.

TrackbaU

TrackbaU, called trackball in Chinese, is a device that puts a small ball in a fixed hole. The user can use the thumb and forefinger to operate. Control the movement of the cursor on the screen by rolling the ball. Since the trackball can be operated with only finger movements, it is easier and more comfortable to operate than a mouse. The trackball is very suitable for use in a mobile environment. It can be made very small and can be embedded in a computing device. However, the trackball is inadequate compared to the mouse in dragging and dragging operations.

Touchpad

Touehpad, called touchpad in Chinese, was first applied to portable computers. The touchpad is a small, touch-sensing rectangular device. Used on laptops. The touchpad technology is a bit like the combination of a touchscreen and Traekball. You can control the cursor on the screen by dragging your finger on the trackpad. There are two ways to implement the selection and determination operations on the trackpad: one is an external button, and the other is a double-click on the trackpad with a finger.

Touch screen

Touch screen technology is to add pressure or optical sensing medium to the display screen. This is used a lot on handheld computer devices. By pressing, pressing, and swiping with your finger, you can control the cursor movement on the screen to achieve the purpose of operation.

Stylus

The stylus is generally used with a touch screen and looks like a pen. This device appeared to solve the problem that the finger cannot be operated on the small screen. Use a stylus for more efficient and comfortable input operations.

Gestures, eye movements, and voice

Gesture operations mostly use gloves and sensing devices to achieve input functions. Gesture input is very suitable for mobile input, but the cost of a gesture input device is too high. Eye tracking uses sensors to identify and track eye movements to determine visual direction. Eye tracking (eye-tracking) is also called eye tracking (tracking) tracking, eye movement measurement. The operations of the voice input type are mainly focused on GUI operations such as menus and some special commands.

2) Text input device

The text input device is complementary to the pointing device. The keyboard is the most commonly used text input device for computers. From the earliest typewriter to the later generation of QWERTY cloth, mobile computing put forward new requirements for the development of the keyboard [27]. Since the keyboards of the early desktop computing were placed on a flat surface and input was performed in a relatively static state, the requirements for keyboard size and operation mode were relatively low. Mobile computing needs to use the keyboard in any state and anywhere, so a series of requirements are made for the size, shape, operation mode, carrying method, and input efficiency of the keyboard. Early mobile input devices were mostly miniaturized and streamlined QWERTY keyboards before being used [28]. The emergence and popularity of handheld computing devices has led to the development and popularity of touch screens, styluses, and soft keyboards. The advent of language and image input has made text input technology move towards the multimedia age.

Soft keyboard

Soft keyboard is not a physical keyboard, it is an application of touch screen technology. Through the touch screen technology, the keyboard is simulated on the screen and the input is realized. It can be operated like a normal keyboard. The size, shape and position of this keyboard can be adjusted arbitrarily. A significant feature of the soft keyboard is that it can be changed according to the user's personal preferences.

Data gloves

Data gloves are usually made of a material with a certain elasticity, and sensors are arranged at the joints for detecting finger bending, abduction, and wrist movements. When the operator puts on the data gloves, the computer can obtain the information about the bending, abduction and hand shape of the finger by detecting the output of each sensor. By using a three-dimensional tracking device placed on the wrist, information such as the position of the hand relative to the transmitter and the orientation of the hand will be obtained. From the current research situation of data gloves, there is still a big gap between the accuracy and harmony of data gloves and humans in operation. First, the main technical goal of data gloves is to enable the natural movements of human hands under the command of the brain to be expressed with data. However, due to the existence of gloves, the contact measurement structure deviates from the original nature to a certain extent. Secondly, research on hand feedback is quite slow. In fact, haptic feedback is often related to force feedback. Therefore, it is quite difficult to generate mechanical feedback independently. At present, haptic research in virtual reality is often carried out through the interdisciplinary synthesis, that is, to model force feedback based on the experience of biomechanics, psychophysics, neurobiology, and the characteristics of the controlled virtual object. Due to the existence of soft tissue in human hands, the accuracy of contact measurement is also greatly affected. This first manifests itself in the inability to control the installation of the sensor. In addition, the strong coupling of sensor readings caused by soft tissue also makes the decoupling process more complicated. The reduction in measurement accuracy caused by them will also significantly affect the feedback of hand feel. Finally, as far as the currently applied products are concerned, the mission of data gloves is still not good in terms of life, reliability, and space tracking accuracy. Its performance and price are also more expensive than other computer peripherals.

Handwriting recognition

As far as proficiency is concerned, handwriting recognition has significant charm in text input. Ideally, a handwriting recognition system is as simple as writing on paper. Anyone can use this device without additional learning, and the input speed is comparable to that of QWERTY beginners. But in the early stages of development, character recognition was also difficult. There are two main input methods for handwriting recognition systems. The first is to write directly on the screen. Although this input method does not take up much space, your hand will cover a part of the screen when writing, which is not conducive to continuous interaction. The second way is to write on a special tablet. This avoids the problem of hand obstruction when writing. From the perspective of recognition rate, handwriting recognition is still not perfect. It is generally agreed that handwriting recognition can be widely accepted only when the accuracy of handwriting recognition reaches or exceeds 97%. The recognition rate of isolated printed characters is 96.8%. One of the advantages of the handwriting recognition system is its ability to collect and process information in real time.

Speech Recognition

From some aspects, voice input is an ideal text input method. It is free to use and interacts naturally. It can be used in almost any environment and occasion. Recognition accuracy is one of the basic indicators of a speech recognition system. Not only can the system accurately recognize words, it should also have the ability to filter out unqualified and incorrect text inputs [29-30]. Therefore, the system should have a rejection value. In speech recognition, in order to reduce the recognition error, it is necessary to set the relevant rejection threshold to control the error rate. Too small a rejection threshold will result in greater false acceptance (replacement or rejection errors), which may cause harmful failures, such as confusing "read files" and "delete files." At the same time, setting the threshold too high will cause greater false rejection (deletion error), so whether the user ignores the input or copies the data will find it difficult to decide. Therefore, for a speech recognition system with insufficient accuracy, it must have a good way to deal with errors. In the work environment, mobile computers are mostly used for input tasks such as inventory, damage control, or communication tasks. In either case, voice control is very useful, which also allows users to free their hands to do other things while working. Audio text input is ideal in these situations.

3) Display output device

The display is a terminal display device for various video signals and computer data information. It is the face of a computer and the main output means of human-computer interaction. Its types will be diversified. With the rapid development of science and technology, various new display devices with different characteristics continue to appear.

Cathode ray tube type direct view display

The shadow mask type single-gun self-convergence color picture tube uses an electron beam to bombard phosphors at high speed in a vacuum tube to emit light. The shadow mask is its color selection mechanism. Cathode voltage excitation is its image modulation method. Electron beam scanning is its addressing method and has a history of more than 50 years. At present, although CRT displays have the characteristics of high brightness, high contrast, high definition, large viewing angle, small inertia, no moving image display, etc., they are not suitable for mobile output due to their large size, large power consumption, and heavy weight. system.

LCD Monitor

The liquid crystal display has the smallest grating geometric distortion and non-linear distortion, and the position and tilt of the grating are not affected by the geomagnetic field. It is small in size, light in weight, and low in power consumption; but it has a small viewing angle, large inertia, fast moving image display speed, and small screen brightness.

LCOS projection display

Liquid crystal is poured between the upper transparent conductive glass and the lower single crystal silicon wafer, and a control circuit is fabricated under the single crystal silicon wafer to control the working state of each liquid crystal pixel. LCOS projection display has high brightness and high definition, but the yield is low, the price is high, the chip manufacturing is difficult, and the life of the projection lamp is a problem.

OLED display

OLED is a new type of display technology that uses organic semiconductor materials and light-emitting materials to emit light under current drive. It is generally considered to be the most promising display technology. Its invention process is simple, the raw material consumption is low, and the manufacturing cost is low; self-emitting, no backlight, low driving voltage; image geometric distortion, small nonlinear distortion, sharpness, color and Consistent full screen, no focus and convergence issues; long life of all solid state devices; fast response.

2.2. Principle of Adaptive Endpoint Detection of Seismic Signals Based on Human-Computer Interaction Technology

(1) Principle of adaptive endpoint detection for seismic signals

Seismic signals are non-stationary random signals, that is, their correlation function or power spectral density changes with time. However, when a signal of length S is divided into small intervals ATUSF of length T, within each small interval The signal can be approximated as a stationary random process H. We are processing based on the generalized stochastic stationary assumption of the signal in the interval.

For two random processes, if they have the same or similar autocorrelation function, the power spectrum structure of the two signals will be the same or similar, and the two signals can be considered to have strong similarity. For a generalized stochastic stationary process s (n), its autocorrelation function is defined as:

$$R(l) = E[s(n)s(n+l)] = \lim_{N\to\infty}(1/2N)\sum_{n=-N}^{N} s(n)s(n+l) \tag{1}$$

In seismic signal endpoint detection, although the seismic signal is non-stationary, after truncation, a short-term autocorrelation function can be used:

$$R_w(l) = [1/(N-l)]\sum_{n=0}^{N-l-1} s(n)s(n+l) \tag{2}$$

Its average value is:

$$E[R_w(l)] = [1/(N-l)]\sum_{n=0}^{N-l-1} E[s(n)s(n+l)] = R(l) \tag{3}$$

Its variance:

$$D[R_w(l)] = E\{[R_w(l) - R(l)]\} \tag{4}$$

When s (n) is zero mean and Gaussian white noise with variance σ², it is easy to obtain:

$$D[R_w(l)] \approx [1/N-l]^2\sigma^4 \tag{5}$$

The above formula shows that when $l \le N$, the variance is small, and when $l \to N$, the variance is large.

Assuming that the two stationary random processes $s_0(n)$ and $s(n)$ have short-term autocorrelation functions of $R_0(l)$ and $R_w(l)$, respectively, they are referenced and defined:

$$\lambda = \sum_{l}[R_w(l) - \alpha R_0(l)]/R_w{}^2(l) \tag{6}$$

Among them, when $\alpha = \sum_l [R_w(l) - \alpha R_0(l)] / R_w{}^2(l)$, λ obtains a minimum value, and at this time λ is called the similarity distance of the autocorrelation functions of these two random processes. It can be found that when λmax = 0, the existence of α satisfies $R_w(l) = \alpha R_0(l)$ for any l, that is, the two signals are considered to be of the same type; when λmax = 1, the two signals are orthogonal, that is, $\alpha = 0$ believes that the similarity between them is the most weak.

Therefore, the λ value objectively reflects the similar distance between signals, and it can be used for signal endpoint detection. For each seismic record, before the signal waveform, the station noise floor of tens of s must always be provided. Let the autocorrelation function of the noise model be $R_0(1)$. Consider an actual seismic record data as two states: state 0 and state 1, state 0 is no seismic signal, that is, the noise floor of the station:

$$y(n) = w(n) \tag{7}$$

State 1 is the seismic signal record of the station:

$$y(n) = s(n) + w(n) \tag{8}$$

Among them, $w(n)$ is the noise floor of the seismic station, and $s(n)$ is the seismic signal.

At state 0, $R_w(l) = R_N(l)$ and $R_N(l)$ are short-term autocorrelation functions of $w(n)$. If the same signal as the noise model is $R_N(l) = \alpha R_0(l)$, then λ is the smallest, indicating that the measured signal is most similar to the noise model at the moment

$$E[\lambda_0] \cong \sum_l E[R_N(l) - \alpha R_0(l)]^2 \Big/ E\left[\sum_l R_N{}^2(l)\right] = \sum_l D[R_N(l)] \Big/ \sum_l \left\{\alpha^2 R_0{}^2(l) + D[R_N(l)]\right\} \tag{9}$$

For white noise, there is

$$E[\lambda_0] \cong \sum_l \left[1/(N-l)^2\right] \Big/ \left\{1 + \sum_l 1/(N-l)^2\right\} \tag{10}$$

In state 1, $R_w(l) = R_s(l) + R_N(l)$ and $R_s(l)$ are composed of two parts, $R_s'(l)$ and $rR_0(l)$, and they are positively intersecting, then the above reasoning can be obtained:

$$E[\lambda_1] = \left[1 + \frac{\sum_l (r+\alpha)^2 R_0^2(l)}{\sum_l R_s^2(l) + \sum_l \frac{\alpha^2 \sigma^4}{N-l}}\right] \tag{11}$$

Among them, $E[\lambda_1]$ mainly depends on:

$$\left[\sum_l R_N^2(l) \Big/ \sum_l R_s^2(l)\right] \times \left\{(1 + r/\alpha)^2 \Big/ \left[1 - r^2 \sum_l R_0^2(l) \Big/ \sum_l R_s^2(l)\right]\right\} \tag{12}$$

Observation can be found: the fourth term of formula (11) is approximately the square of the inverse of the signal-to-noise ratio, and the sixth term depends on the similarity β of $R_s(l)$ and $R_0(l)$, and the similarity β is defined as

$$\beta = r^2 \sum_l R_0^2(l) \Big/ \sum_l R_s^2(l) \tag{13}$$

(2) Research on seismic signal phase adaptive correction method

In the past, the general method is to directly add different geophone records corresponding to the receiving channel in the time domain or simply remove the time difference of the entire channel or even adjust the amplitude and superimpose it to obtain a synthetic seismic record. A large number of facts have shown that the superposition method is not as fidelity as the reconstruction method. The scientific method is to achieve accurate reconstruction of seismic signals by phase correction methods of high and low frequency signals in the frequency domain. The basis of seismic signal phase correction is based on seismic signal phase correction based on the difference in phase characteristics inherent to the geophone. It has been proved that phase correction plays an important role in the frequency-received signal reconstruction technique. In the past, phase correction methods with fixed parameters were affected by factors such as old and new detectors, coupling differences, embedded patterns, and different numbers of combinations, which would cause the phase differences recorded by different types of detectors to be inconsistent with theory or when shipped. Therefore, it is necessary to use multiple actual data to carry out adaptive correction method research to ensure the good effect of signal reconstruction.

1) Actual acquisition of three parameters

The three parameters calculated using the characteristic point data of the single gun spectrum curve are shown in Table 1. From this, it can be seen that the calculation results are significantly different from the results usually selected in the past, indicating that the method that was previously selected from multiple sets of artificially given parameters still has poor adaptability. Therefore, the adaptive phase correction method in signal reconstruction is studied. has practical significance.

Table 1. Three parameters calculated by using characteristic point data of single gun spectrum curve

Parameter	D_{01}	D_{02}	K
Numerical value	0.381	0.546	0.608

2) Three-parameter calculation process for phase adaptive correction

The calculation of D01 and D02 in the three-parameter formula for phase correction is not very intuitive, and it is difficult to use an explicit expression. The implicit expression can be solved using an iterative method. The convergence of this iterative formula is not discussed here. The actual trial calculations based on many records can meet the required results. The number of iterations is not large. Generally, the accuracy of 0.0001 can be reached within 10 times, and the convergence speed is faster. The seismic signal phase adaptive correction method is implemented by means of the entire seismic signal reconstruction software. In the original application software, 5 parameters need to be given, including ω_{01}, ω_{02}, K, D_{01}, and D_{02}, etc., and our phase adaptive correction method must calculate the three parameters K, D_{01}, and D_{02} in advance, and write parameter calculation functions. Therefore, the phase correction calculation formula of the whole work area is determined, thereby enhancing the adaptability of the phase correction.

The three-parameter calculation process of phase adaptive correction specifically includes four steps:

The first step: collect test data of different types of geophone comparison tests performed before production;

The second step: making the spectrum recorded by the high and low frequency detectors;

Step 3: Read the amplitude of the characteristic points on the spectrogram, and compile it into a text file with the natural frequency parameters of the detector;

Step 4: Run the three-parameter calculation function (or module) for phase correction, and output 5 parameters, including ω_{01}, ω_{02}, K, D_{01}, and D_{02}.

3. Experiments

3.1. Algorithm Implementation

In this paper, the full-band vertical (BHZ) signal (sampling frequency is 20 Hz) of the three-way station is used for analysis and detection with 20 points as a frame. It can be known from equation (4) that the variance of short-term autocorrelation mainly depends on $1/(N-l)$. Therefore, the larger the l, the larger the variance. Generally, an autocorrelation function of 2/5 frames (that is, 8 points) is used for decision, and the data frame is moved by 5 sampling points at a time. The specific implementation steps of the algorithm are as follows:

1) Take 20 frames (400 points) from the sampling signal without seismic signal (such as the data header part of the seismic record), find its autocorrelation function according to formula (1), and establish the noise model $R_0(l)$.

2) Find the short-term autocorrelation function for each frame signal according to formula (2);

3) Calculate the similarity distance λ of the autocorrelation function according to formula (6).

4) Calculate the mean E and variance σ of the similarity distance λ of the autocorrelation function of the first 20 frames of signals, and then determine the threshold;

5) Determine the seismic signals according to steps 3) and 4). Generally, E ± 0.8σ is the threshold value. If 4 consecutive frames are greater than the threshold value, and the frame distance is 20, the frame signal does not exceed 5 ×20 frames, which is the start frame of the seismic signal.

6) If the start frame of step 5) is 20 frames away from the beginning of the signal, the signal is 5 ×20 frames above ground. Since the original noise model may fail after a long time interval #, the start point is detected at this time. Before that, we took 20 frames of signals one by one in sequence, and established a new noise model according to algorithm steps 1) to 4), so that the noise model adaptively tracked the change in signal noise, and then continued to detect.

7) When detecting the end frame of the earthquake, perform actions similar to steps 5) and 6). Only when the signal is more than 20 frames away from the beginning 20 frames, the signal model is re-established.

8) Determination of starting point and ending point. In the start and end frames, 5 consecutive points that are greater than (or less than) the threshold are determined as the endpoints (start or end) of the signal.

3.2. Simulation Experiment

1) First, use the simulated seismic signal (superimposed by 5 FM exponential functions) for experiments. The total length is 2000 sampling points. The starting point and ending point of the effective signal are the 750th and 1800th points, respectively.

2) Using the above algorithm, endpoint detection was performed on a group of seismic record signals, and comparison was made with manual detection methods to analyze the experimental results.

3) Multi-type geophones are used to compare the received wide-line two-dimensional seismic data to the seismic signal phase adaptive correction technology. The correction process is for a single shot record. In order to make the comparison and analysis of the results simple, choose from many single shots. Records of two shots with different doses, and only consider the processing results of three types of detectors, 5Hz, 40Hz and 60Hz.

4. Discussion

4.1. Results and Analysis of Adaptive Endpoint Detection of Seismic Signals Based on Human-Computer Interaction Technology

Experiments were performed using simulated seismic signals (superposed by 5 FM exponential functions). The original signal and the experimental signal with noise of 6dB, 0dB and -3dB are shown in Figure 3.

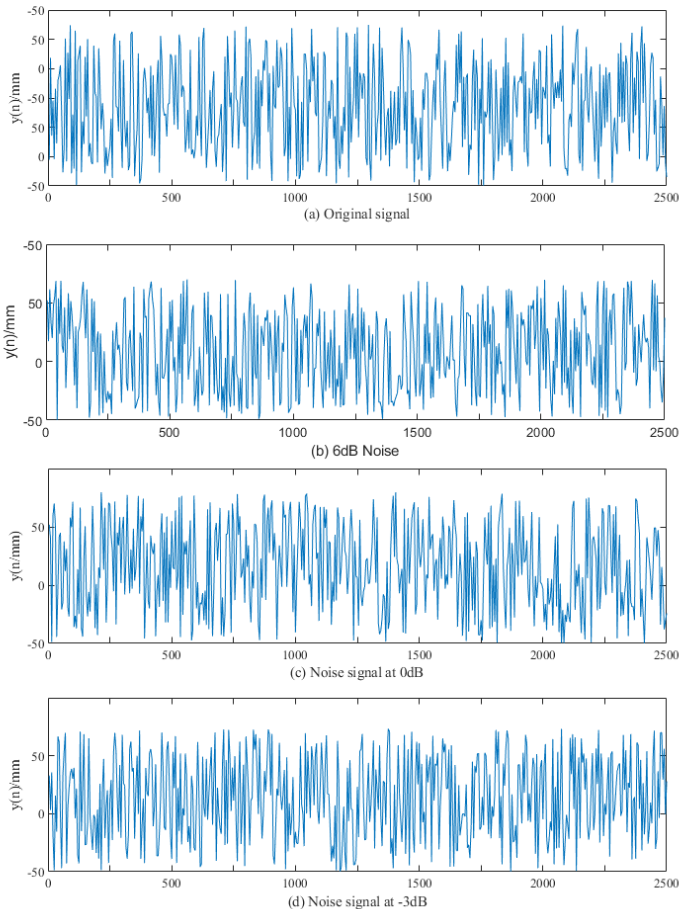

Figure 3. Simulated seismic signal for experiment

It can be known from Fig. 3 that the total length of the simulated seismic signal is 2000 sampling points, and the starting point and ending point of the effective signal are the 750th and 1800th points, respectively. The simulated seismic signal and Gaussian white noise were respectively synthesized into multiple experimental signals with different signal-to-noise ratios. Figure 3 shows the original signals and the experimental signals with noise of 6dB, 0dB, and -3dB, respectively.

The similarity distance algorithm and the artificial detection method of the correlation coefficient are used to perform endpoint detection on this set of simulated seismic signals. The experimental results of the two detection methods are shown in Table 2 and Figure 4.

Table 2. Comparison of endpoint detection results of seismic signal

Simulated seismic signal	Article method		Manual inspection method	
	Starting point	Termination point	Starting point	Termination point
Original signal	750	1800	750	1800
Noise signal (10dB)	750	1800	761	1794
Noise signal (6dB)	752	1801	795	1789
Noise signal (3dB)	756	1797	818	1752
Noise signal (0dB)	774	1785	847	1705
Noise signal (- 3dB)	796	1774	821	1705

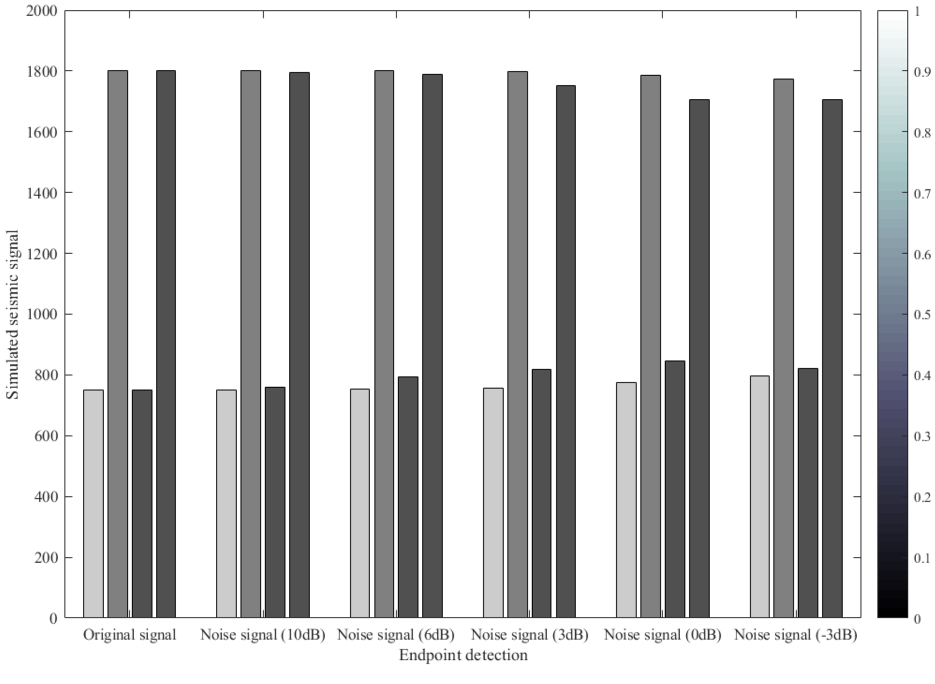

Figure 4. Comparison of endpoint detection results of seismic signal

Combining Table 2 and Figure 4 shows that because the artificial detection method uses the magnitude of the noise amplitude as the threshold for signal endpoint detection, the detection results of its endpoints have a great relationship with the signal-to-noise ratio, and it is difficult to accurately locate the signal; similar distances based on correlation coefficients The detection method of seismic signal endpoints is based on the similarity of the signals, so it is less affected by the change of the signal's signal-to-noise ratio (under certain signal-to-noise ratio conditions), and its detected starting and ending points are more accurate.

4.2. Comparison of Adaptive Correction Results of Single Shot Recording Phase Based on Adaptive Endpoint Detection of Seismic Signals Based on Human-Computer Interaction Technology

First analyze the results of the 5Hz detector record correction to 40Hz. The single shot record before correction is shown in Figure 5.

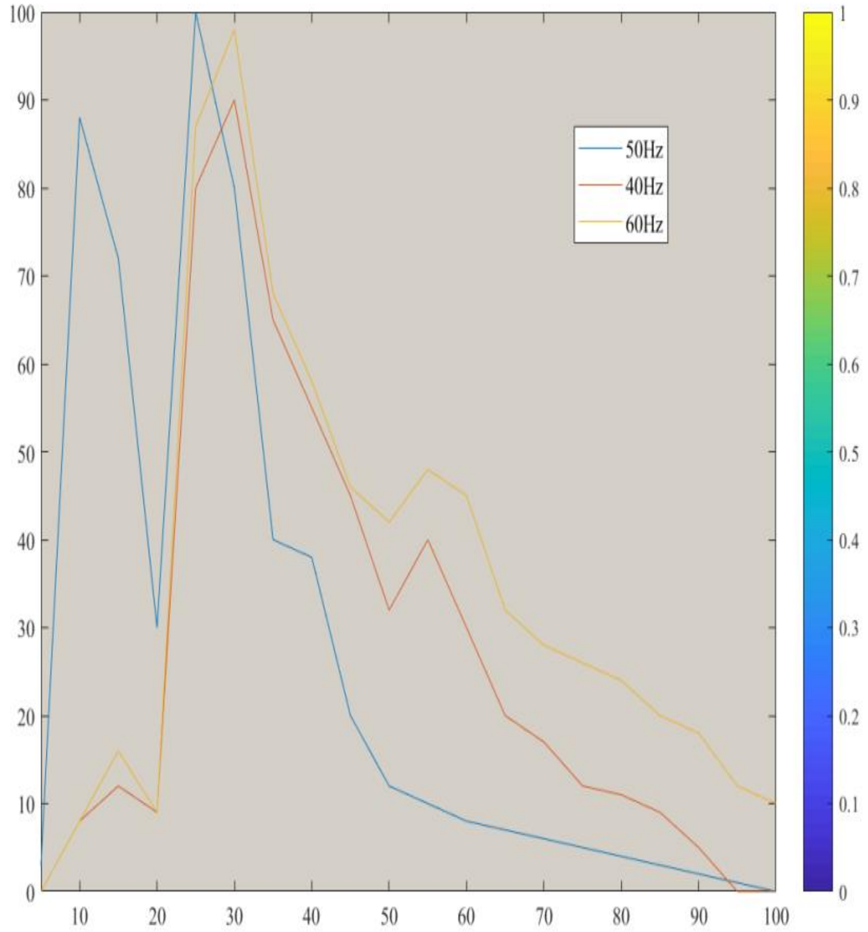

Figure 5. Seismic record and spectrum of the 265th gun

The 265th shot of the 5Hz seismic record is corrected with fixed parameters and adaptively corrected to 40Hz.

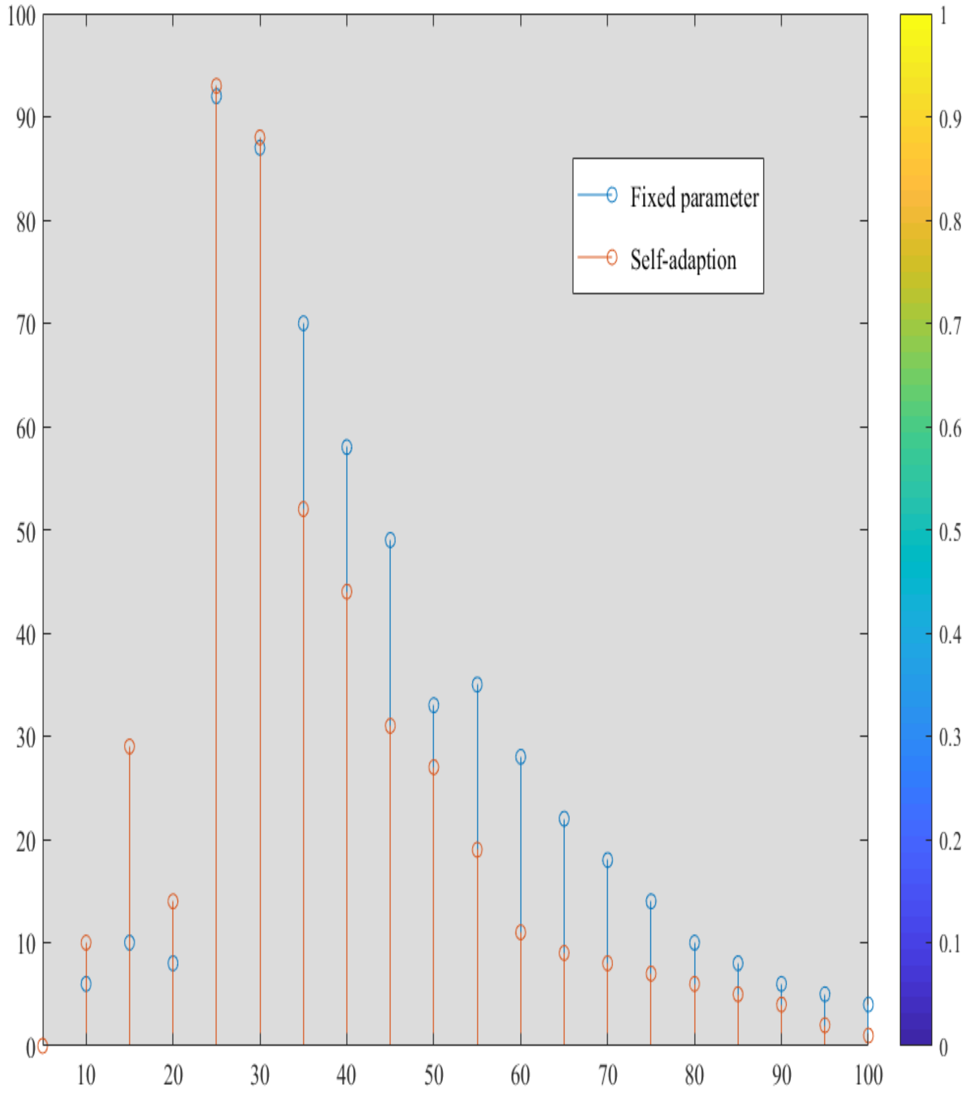

Figure 6. 5Hz seismic record of 265th gun corrected to 40Hz

It can be seen from Fig. 5 and Fig. 6 that after calibration, the expected purpose is basically achieved. Compared with the original record of 40Hz, the fixed parameter correction result is more similar to the original record of 40Hz, especially the spectrum difference is small. However, as far as fidelity is concerned, the fixed parameter correction results change the frequency characteristics of the 5Hz record greatly.Although the phase and the dominant frequency are aligned with the 40Hz original record, the fidelity is reduced to a certain extent; and the adaptive correction As a result, not only the phase and video frequency can be matched with the original recording of 40Hz, but also maintain the basic characteristics of the frequency of the 5Hz recording, and still have a certain level of low-frequency information, so it has good fidelity.

Analyze the 5Hz detector to record the results corrected to 60Hz. The fixed-parameter correction and adaptive correction to 60Hz for the 265th gun 5Hz seismic record are shown in Figure 7.

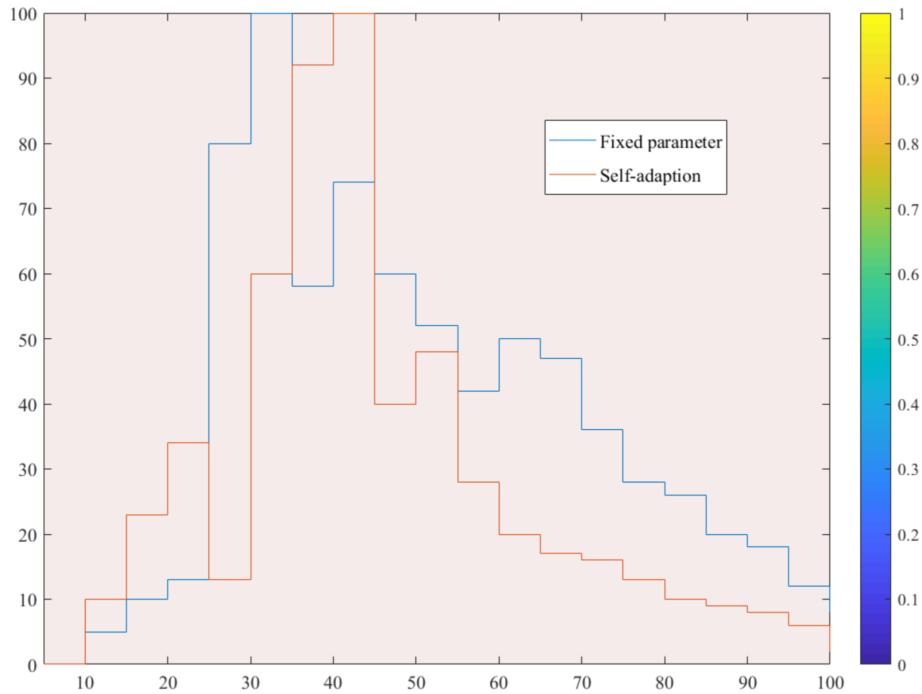

Figure 7. Record of 5Hz seismic record corrected to 60Hz of 265th gun

It can be seen from FIG. 7 that after the correction, the expected purpose is basically achieved, and it is similar to the original record of 60Hz. In contrast, the correction result of the fixed parameter is more similar to the original record of 60Hz, especially the spectral difference is small. However, as far as fidelity is concerned, the fixed parameter correction results change the frequency characteristics of the 5Hz record.Although both the phase and the dominant frequency can be matched with the 60Hz original record, the fidelity is reduced to a certain extent; and the adaptive correction result Not only the phase and video frequency can be matched with the original 60Hz record, but also maintain the basic characteristics of the frequency of the 5Hz record, and still have a certain intensity of low-frequency information, so once again it shows that the adaptive correction has good fidelity.

The endpoint detection accuracy and model training time of several algorithms are used as evaluation indicators of performance, and simulation experiments are performed for each algorithm. The average value is repeated 20 times as the final detection result. The results are shown in Table 3.

Table 3. Performance comparison of each detection algorithm

Detection algorithm	Accuracy	Training time(s)
Algorithm 1	94.87%	0.031
Algorithm 2	95.91%	4.53
Algorithm in this paper	96.11%	3.29

As can be seen from Table 3, in the real environment, the adaptive endpoint detection algorithm for seismic signals based on human-machine interaction technology proposed in this paper is still the best in endpoint detection accuracy, and has reached a high level, reaching 96.11%. Although the algorithm in this paper is unsatisfactory in model training time, in fact, the training time can often be ignored, so the algorithm in this paper still has high desirability.

5. Conclusion

Earthquake disasters have caused a lot of irreversible damage to people's lives and property. Based on this, this paper proposes research on adaptive endpoint detection of seismic signals based on human-computer interaction technology. This method can detect valid signals and locate their endpoints to realize automatic detection of seismic signal endpoints. At the same time, it will provide accurate time parameters for identifying the nature of events using the "seismic seismic phase energy ratio" criterion.

Based on human-computer interaction, this paper proposes the concept of similar distance of signal autocorrelation coefficients, proves and discusses the distinguishable "autocorrelation similarity distance" between noise and signals, and concludes seismic signals based on correlation coefficients. The endpoint detection method, and the specific implementation steps of the algorithm are given. The method for determining the detection threshold is described. The experimental detection results obtained by using this method and the artificial detection method are compared. The experimental results in this paper show that the method in this paper has a comparative High accuracy.

In addition, this paper proposes and successfully implements an adaptive phase correction method based on the signal reconstruction technology with fixed parameter correction, making the new seismic signal reconstruction technology highly adaptable, indicating that the adaptive phase correction method has Good information fidelity. The seismic signal reconstruction technology based on the adaptive phase correction method can well realize the organic synthesis of high and low frequency synchronous recordings, and can obtain ideal wideband recordings with broad application prospects.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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