Single-Channel Blind Source Separation and Its Application on Arc Sound Signal Processing

Wenjing Ren, Guangrui Wen, Riwei Luan, Zhe Yang and Zhifen Zhang

Abstract Welding arc sound signal is an important signal in intelligent welding diagnosis, due to its informative, noncontact, easy collected. However, due to the interference of ambient noise, the arc sound signal is highly complex and noisy, which seriously limits the application of arc sound signals. In this paper, a single-channel blind source separation (BSS) algorithm based on the ensemble empirical mode decomposition (EEMD) is proposed to purify and denoise the arc sound signals. First, EEMD is used to decompose one channel signal to several intrinsic mode functions (IMFs). Second, principal component analysis (PCA) is used to reduce the multidimension IMFs to low-dimension IMFs, which are regarded as the virtual multichannels signals. Finally, independent component analysis (ICA) separates the virtual multichannels signals into target sources. The approach was tested by simulation and experiments. The simulated results show that signals separated from mixed signal using this approach highly match the source signals that make up the mixed signal. Moreover, experimental results indicated that the source signals of arc sound were effectively separated with the environmental noise signals. The statistical characteristics of the spectrum in 5–6.5 kHz band extracted from the arc sound source signals can accurately identify the two types of weld penetrations.

Keywords Single-channel blind source separation · EEMD
Arc sound signal · Intelligent welding diagnosis

W. Ren · G. Wen · R. Luan · Z. Yang · Z. Zhang (✉)
The Research Institute of Diagnosis and Cybernetics, Xi'an Jiao Tong University, Xi'an, China
e-mail: zzf919@xjtu.edu.cn

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1 Introduction

As an accompanying signal of welding process, arc sound signal carries abundant information of welding physical parameters. Experienced manual welders can obtain higher welding quality through the feedback of arc sound [1]. Welding arc sound signal is the interaction of energy change, arc volume fluctuation, protective gas flow, molten pool shape, and so on [2–5], thus creating a tight correspondence between arc sound signals and those parameters. Recently, acoustic signals are widely used in welding process defect detection and welding dynamic monitoring. Emad [6] reveals the relationship between arc sound signal and such penetration states as partial penetration, full penetration, and burn through. Power spectrum density (PSD) features were extracted from arc sound signals, and three welding states were effectively identified by means of neural network. Lv [7–9] realizes the recognition of welding arc length and penetration state, using time and frequency domain characteristics extracted from the sound signals of gas tungsten arc welding (GTAW). Zhang [10] using support vector machine (SVM-CA) estimate the different weld penetrations, local caving, and porosity of GTAW, based on the fusion of voltage, sound, and spectral signals. And a set of multi-signals preprocessing, feature extraction, dimensionality reduction, and fusion defect pattern recognition methods were put forward.

The key to the accuracy of welding defect detection is the quality of the original signal. As for the complex working environment, the original arc sound signal is usually a superposition of many source signals such as arc, welding machine, and environment. As a result, the original arc sound signals are complex and have low signal-to-noise ratio. Therefore, effective noise reduction is greatly important to improve the accuracy of welding defect detection. At present, the widely used methods for denoising are noise filtering, time domain average, etc. [11]. But these methods cannot remove the environmental noise whose frequencies are low and overlapping with arc sound signal. Blind source separation (BSS) is a dominant technique for separating the multivariate signals into different source independent components. The independent component analysis (ICA) is the main method for BSS. ICA separates useful signals from noises and concentrates them into the corresponding independent components. Then the noises can be easily reduced. It has been applied in various fields such as rotors fault diagnosis, electroencephalography (EEG), etc. [12, 13], but few literatures report the application on welding audio signal. The biggest limit of ICA is that if there are fewer channel signals than sources signals, ICA cannot guarantee efficient separations and useful information may be lost.

In this paper, a novel approach of single-channel BSS based on EEMD is presented. To overcome the limitation of the ICA, EEMD has been proposed to assist ICA for improving the performance of denoising. The single-channel mixed signal is decomposed first by EEMD to IMFs. Then PCA is used to reduce the IMFs to principal components (PCs). Finally, ICA separated the PCs into the target source signals. The effectiveness of the approach is verified by simulation and actual arc sound signals. The results proved that the proposed approach is conducive to the characteristics extraction of arc sound signals. Eight statistical characteristics extracted from the spectrum of separated signal u_1 can distinguish the partial penetration from the full penetration effectively.

2 Single-Channel Blind Source Separation

2.1 Blind Source Separation

BSS is used to separate source signals from one or more observations with an unknown mixture process of sources. ICA is a common method for BSS and is widely used in many disciplines [14]. In this method, source signals are separated from observations based on the statistical independence hypothesis of sources, without any prior knowledge. The ICA mathematical model is shown in Fig. 1.

Where $s(t)$ ($s(t) = [s_1, s_2, \ldots, s_m]^{\mathrm{T}}$) is source signals. $x(t)$ ($x(t) = [x_1, x_2, \ldots, x_n]^{\mathrm{T}}$) is original signals, which is linearly combined from $s(t)$ by a mixing matrix, expressed as $x(t) = A_{n\times m}\cdot s(t)$.

Under the condition that $x(t)$ is known, $A_{n\times m}$ and $s(t)$ are unknown, ICA is the approximate estimation of separating source signals $s(t)$ by optimizing the separation matrix $W_{n\times m}$. The optimal $W_{n\times m}$ should make sure the separated signals have strongest independence.

Therefore, ICA is essentially an optimization problem, which mainly includes two aspects: the one is to establish the optimal objective function to determine the independence standard; the other one is to select the appropriate algorithm to optimize the objective function. According to these two aspects, a variety of ICA methods can be derived. Among them, fast independent component analysis (FastICA) is a widely used and mature algorithm. In this method, the negative entropy maximization standard is used to obtain the most optimal separation matrix [15]. The calculation steps are listed in Fig. 2.

2.2 Single-Channel BSS Based on EEMD

Because of the complex environment in engineering practice, the number of signal sources is difficult to predict. Meanwhile, the multisensors are high cost and hard to

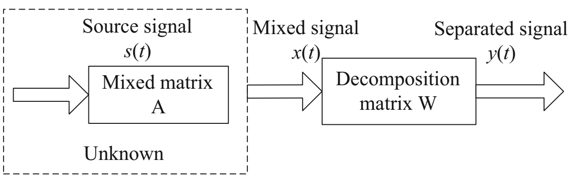
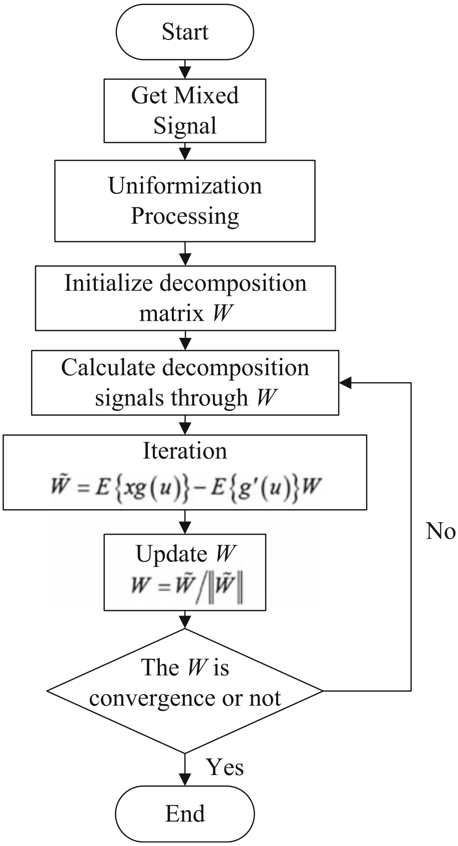


Fig. 1 Mathematical model of ICA

Fig. 2 Block diagram of FastICA



assembly. So the number of sensors is often less than that of signal sources, and even only single-channel signal is collected. In order to realize the single-channel BSS, the single-channel signal should be decomposed to virtual multichannel signals.

Empirical Mode Decomposition (EMD) is a time-frequency analysis method proposed by Huang in 1998 [16]. It decomposes the signal into a series of Intrinsic Mode Functions (IMFs) based on the local time characteristics of signals. Thus, the complex signal is reformed into multiple single components whose instantaneous frequencies are meaningful. EMD can adaptively decompose the signals, so it is quite suitable for decomposing the nonlinear and nonstationary signals. A significant drawback of EMD is that the decomposed signals have aliasing in frequency.

EEMD is an improved EMD algorithm [17]. The aliasing is restrained by adding white noises to original signal before decomposing. The decomposed results, which have added different white noise, are averaged to eliminate the white noises in IMFs. Because of the uniform distribution of white noise scale, it can not only smooth the abnormal disturbances such as pulse interference but also can provide evenly distributed random scale for signals, and effectively suppress the frequency aliasing. The steps of the EEMD algorithm are described as follows.

(a) Adding Gaussian white noise $\omega(t)$ to $x(t)$,

$$X(t) = x(t) + \omega(t) \tag{1}$$

(b) Decompose $x(t)$ to IMFs by using EMD,

$$X(t) = \sum_{n=1}^{N} c_n(t) + r_N(t) \tag{2}$$

where, $c_n(t)$ the nth IMF; N is the number of IMFs in each decomposition; $r_N(t)$ is the residual volume after decomposing.

(c) Repeat steps a and b M times, but adding different Gaussian white noise each time. The final IMFs are the average of M times IMFs:

$$c_n(t) = \frac{1}{M} \sum_{i=1}^{M} c_{in}(t) \tag{3}$$

where, $c_{in}(t)$ is the nth IMF decomposed by the ith times EMD. As the final IMFs decomposed by EEMD are usually multiple, which will cause high iteration numbers and slow convergence when multiple IMFs are directly used for ICA. To solve this problem, PCA is used to reduce the number of the IMFs. The principal components which contribute most are selected and regarded as the virtual multi-channel signals. Then FastICA is processed on them to obtain the separated source signals. Then the single-channel BSS is proposed and its total principle is as follows (Fig. 3):

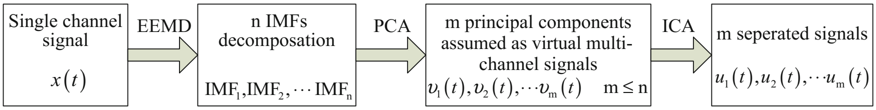


Fig. 3 Total block diagram of single-channel BSS

3 Simulation Analysis

In order to verify the effectiveness of this proposed method, simulations are carried out. First, three source signals, labeled $s_1(t)$, $s_2(t)$, $s_3(t)$, are established and mixed into a single-channel mixed signal $x(t)$.

$$s_1(t) = 5 \times \sin(2 \times \pi \times 450 \times t) \cdot \mathrm{e}^{-5000\left((t-\mathrm{round}(t\times 15)/15)^2\right)} \tag{4}$$

$$s_2(t) = \sin(2 \times \pi \times 100 \times t) \tag{5}$$

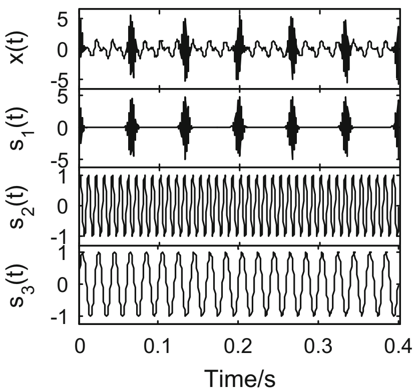
$$s_3(t) = \sin(2 \times \pi \times 50 \times t) \tag{6}$$

$$x(t) = 1.1s_1(t) + 0.7s_2(t) + 0.85s_3(t) + 0.1n(t) \tag{7}$$

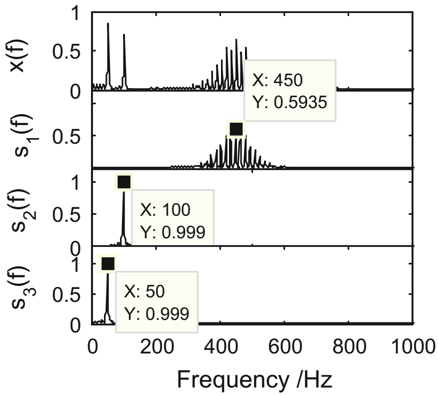
where $n(t)$ is a noise signal. The signals are simulated at a sampling rate of 2048 Hz. Their time domain and spectrum graphs are shown in Fig. 4.

According to the process scheme showed in Fig. 3, the mixed signal $x(t)$ is decomposed to nine IMFs by EEMD, in which the variance of the white noise is half the variance of $x(t)$, and the decomposed times (M) is 100. The nine IMFs are reduced to three principal components by PCA, and the cumulative contribution rate of the three principal components is 98.47%. The three principal components are used as the virtual multichannel mixed signals to be processed by ICA. And finally, three separations are obtained, whose time domain and spectrum graphs are shown in Fig. 5.

Comparing the results in Figs. 4 and 5, the separation signals are basically consistent with the source signals. It is proved that the newly proposed method can effectively realize the blind source separating of single-channel mixed signals. The differences of the amplitudes and orders between the separated signals and the source signals are also consistent with the uncertainty of the results separated by BSS.



(a) Time domain



(b) Frequency spectrum

Fig. 4 The time and frequency domain graphs of source signals and mixed signal

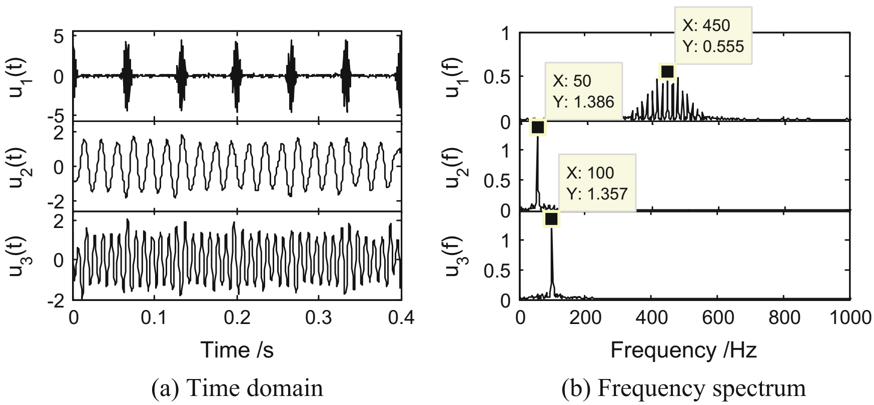


Fig. 5 The time domain and spectrum graphs of separated signals

4 The Welding Arc Sound Signal Processing

4.1 Experimental Data Acquisition

The arc sound signal used in this paper is the single-channel arc sound signals collected during the welding process of aluminum alloy pulsed GTAW. The experimental conditions are shown in Table 1.

The audio sensing system includes an omnidirectional capacitance microphone (MP201) to pick audio signals, and a signal conditioner (MC104) to filter and amplify the signals. The microphone has the frequency response from 20 to 20 kHz. The sound signals are collected with the sampling rate of 40 kHz by a data acquisition card in the computer.

In order to verify the influence of single-channel BSS on welding quality diagnosis, arc sound signals in two states of welding, including partial penetration and full penetration, were collected and processed respectively. Because the base welding current parts are mainly used to maintain the welding arc and contain little welding information. The base level signals are discarded and only peak signals are

Table 1 Experiment conditions and welding parameters

Welding parameters	Value
Pulse frequency (Hz)	2
Peak current (A)	260
Base current (A)	50
Ar flow (L/min)	15
Welding speed (mm/s)	3
Feed speed (L/min)	7
Electrode diameter (mm)	3.2
Duty ratio (%)	50
Material type	LF6 Al alloy

reserved for further processing. To meet the requirement of processing efficiency and accuracy, the signals are divided into several data blocks whose size are 3000 sampling points.

4.2 Arc Sound Signal Processing and Analysis

The time domain graph and spectrum graph of arc sound signals of partial penetration and full penetration are shown in Fig. 6. The frequency spectrum comparison between different penetration states show that the arc sound signal spectrum is mainly concentrated at 0–15 kHz, and the frequency distributions are complex. The frequency characteristics under different penetration states are different, but not significant.

The proposed method of single-channel BSS was used to deal with the welding audio signals. First, the single data block was decomposed to 12 IMFs by EEMD. Then PCA was used to reduce the 12 IMFs to three principal components, whose sum contribution rate was more than 90%. The three principal components were treated as the virtual multichannel signals. The separated signals are separated from those three virtual channel signals through FastICA algorithm. The results are shown in Fig. 7.

Figure 7a, b are spectrums of three separated signals obtained from partial penetration and full penetration welding acoustic signals, respectively. Due to the

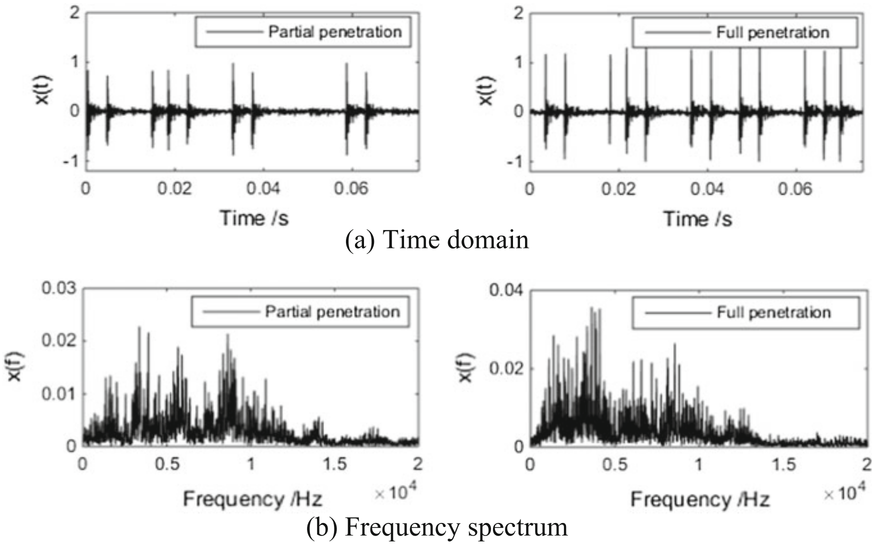


Fig. 6 The time domain and spectrum graphs of the partial penetration and full penetration arc sound signals

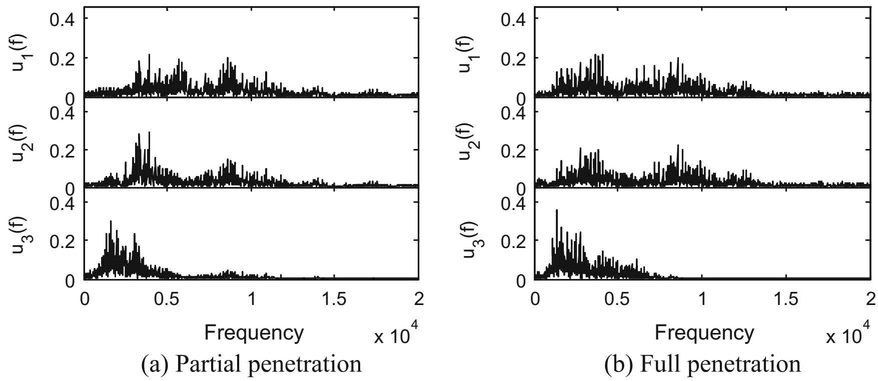


Fig. 7 The spectrum of partial penetration and full penetration

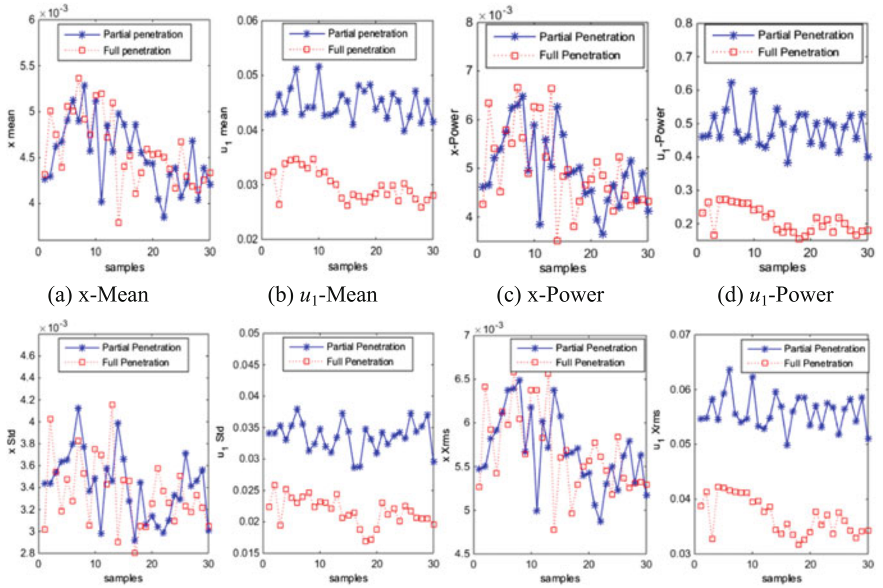
Table 2 The correlation coefficients between each separation and source signals

	u_1(t)	u_2(t)	u_3(t)
Partial penetration	0.926	0.022	0.322
Full penetration	0.977	0.123	0.014

uncertainty of the amplitude and the order of signals separated by BSS, a method is proposed to identify and order each separation according to their characteristics. The correlation coefficients between the each separation signal and the original signal are calculated, and the separation with maximum correlation coefficient is selected as u_1. The remaining two separations are ordered by the frequency of spectral peaks. The separation with higher peak frequency is selected as u_2, and the other is u_3. The separations in Fig. 7 have been sorted. The correlation coefficients between each separation signal in Fig. 7 and the original mixed signal are shown in Table 2.

It can be seen from Table 2 that the separation signal u_1 has a high correlation with the original signal, while the separation signal u_2 and u_3 have very small correlation with the original signal. In Fig. 7, the spectrum of the separated signal u_1 is similar to that of the original signal, while u_2 and u_3 greatly differ from the original signal. These indicate that the separated signal u_1 contains the main welding arc sound information, while u_2 and u_3 are isolated signals other than the audio signal. It is obvious that the spectrum in the middle frequency band (5–6.5 kHz) is remarkable.

Thirty groups of full penetration and partial penetration samples were processed as mentioned above, 15 common statistical characteristics were extracted from the frequency spectrum in the 5–6.5 kHz band of signal separation u_1 to identify different penetration states. The identification results of characteristics extracted from the separated signals were compared with that from the original signals. The results show that the 15 characteristic values extracted from the original signals cannot



(a) x-Mean (b) u_1-Mean (c) x-Power (d) u_1-Power

(e) x-Std (f) u_1-Std (g) x-Xrms (h) u_1-Xrms

Fig. 8 Statistical characteristics of partial penetration and full penetration arc sound signal

distinguish the partial penetration from full penetration. However, for the characteristics exacted from the separation signals u_1, there are eight characteristics can effectively distinguish the two welding penetration status, including the mean, amplitude, energy, variance, root mean square, waveform factor, covariance, and peak value of the spectrum. The identification results of first four characteristics are shown in Fig. 8.

Figure 8 shows that the characteristics extracted from the original signals are irregularly distributed and cannot distinguish the two penetration states. The statistical characteristics of u_1 can effectively distinguish two kinds of welding penetration states. The main reason can be analyzed as follow: As is known, sources of sound emission are ordinarily from the vibration caused by plasma, metal vapor, and cracking in weld zone. This vibration usually has a higher frequency corresponding to the high-frequency component of the arc sound. When the weld penetration changes, the vibration's intensity and features change accordingly, which cause an obvious change of high frequency in the spectrum of arc sound. However, the original audio sound signals contain noises produced by environment, equipment, and so on. The frequency domain information of the welding states is masked by noise frequency. The separation signal u_1 obtained by single-channel BSS is the source signal of arc. Other source signals of environment and equipment are filtered out. So the characteristics of high frequency (around 6 kHz) in the spectrum are highlighted. The statistical characteristic parameters, such as mean and variance, etc. can well reflect the spectral intensity and characteristics. That is why the characteristics mentioned above can be used to effectively identify the welding penetration states as shown in Fig. 8.

5 Conclusion

The single-channel BSS method based on EEMD is proposed for arc sound signal to reduce the environmental noises. In the proposed method, the single-channel signal is decomposed into IMFs by EEMD. Then PCA is used to reduce the IMFs to PCs. Finally, source signals can be separated from the principal components using FastICA. The method's efficiency was verified by simulation as well as real welding arc sound signals. The main conclusions are summarized as follows.

(a) The simulated results show that the separated signals are basically consistent with the source signals making up the mixed single-channel signal, but the order and amplitude of separations are uncertain. Three separated source signals are obtained from the collected single-channel arc sound signals. The sorted separation signal u_1 which has the largest correlation with the original arc sound signal is the source signal of arc sound.
(b) Thirty groups of full penetration and partial penetration arc sound signals were separated by this proposed method, the statistical characteristics of the spectrum in the 5–6.5 kHz band were extracted from the separated signal u_1. Eight statistical characteristics such as the mean amplitude, energy, and so on, can effectively distinguish the partial penetration from the full penetration. But, the characteristics extracted from original signal are irregularly distributed, and cannot distinguish the different penetrations.
(c) The source signal of arc sound can be effectively separated from single-channel signal by the single-channel BSS. After that, the frequency domain characteristics indicating welding conditions become more obviously. High-quality welding arc sound signals are provided for state detection.

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