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In-situ acoustic monitoring of direct energy deposition process with deep learning-assisted signal denoising

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A B S T R A C T

In-situ monitoring is crucial for detecting process anomalies and ensuring part quality in additive manufacturing. Acoustic-based monitoring techniques offer extra benefits such as adjustable sensor setup and lower hardware costs. In the direct energy deposition (DED) process, acoustic signals generated by laser-material interactions carry information about underlying complex physical mechanisms such as melting, solidification, crack propagation, and pore formation. This paper presents a novel acoustic-based *in-situ* monitoring method for the DED process. The raw acoustic signal is made up of laser-material interaction sound as well as noise from machine movement, inert gas flow, and powder flow. A deep learning model is developed to build an end-to-end signal denoising framework to minimize environmental noise and extract the laser-material interaction sound. Audio equalization, bandpass filtering, and Harmonic-Percussive Source Separation algorithm are used to produce a cleaned laser-material interaction sound as the model's ground truth target. Acoustic data is collected from experiments using different DED machines, materials, and varied process parameters to train the deep learning model. The proposed deep learning-assisted signal denoising strategy lays the groundwork for acoustic-based *in-situ* defect detection of the DED process.

1. Introduction

Direct energy deposition (DED) has gained prominence in the aerospace, maritime, and defence industries in recent years due to its distinct benefits in fabrication flexibility and material performance enhancement [1–3]. Despite all the advancements, DED still faces significant challenges in terms of quality consistency and process repeatability. Many defects such as cracking, porosities, and distortions are only attainable through destructive testing, which cannot be employed for in-process monitoring and control systems. The development of in-situ monitoring and adaptive quality enhancement methods is the key to improve the final part quality and efficiency of the DED process [4].

Many recent research efforts have been devoted to developing vision-based *in-situ* monitoring systems for laser additive manufacturing (AM). For example, Kwon et al. [5] presented a deep neural network to classify melt pool images acquired from a high-speed camera to predict different laser power levels during the selective laser melting (SLM) process. Since laser power influences the formation of pores or fractures, which in turn affects the component quality, precise laser power prediction is beneficial for identifying process anomalies. In addition, vision information can be used directly to detect voids [6] and predict porosities [7]. Real-time vision data can also be used to create a closed-loop control system that allows to stabilise the melt pool and improve geometric accuracy [8,9]. Recently, the authors' research team has developed an in-situ surface defect identification approach based on laser-line scanning and an in-process adaptive dimension correction strategy [10–12] for the DED process.

Vision-based monitoring solutions are typically time-consuming and costly to deploy. Acoustic-based monitoring approaches provide additional benefits such as adjustable sensor configuration and lower hardware costs. In the laser-based AM process, acoustic signals generated by laser-material interactions carry information about underlying complex physical mechanisms such as melting, solidification, crack propagation, and pore forma-

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tion. Recently, acoustic-based monitoring methods in the laser powder bed fusion (LPBF) process were reported in the literature, achieving promising results in classifying different materials and process regimes [13], identifying process anomalies with semi-supervised learning [14], and extracting re-usable features to monitor different materials via transfer learning [15]. Since there is no gas flow in the enclosed chamber and little machine movement in the LPBF, external noise has a negligible impact on the acoustic signal, making this only a minor problem for monitoring the LPBF process. The acoustic signal in the DED process, on the other hand, is typically noisier, making analysing the laser-material interaction sound difficult. In the DED process, acoustic-based monitoring is rarely investigated.

To this end, this paper presents a novel acoustic-based *in-situ* monitoring method for the DED process. The raw acoustic signal contains laser-material interaction sound, as well as noises from machine movement, inert gas flow, and powder flow. A deep learning model is developed to build an end-to-end signal denoising framework to minimize environmental noise and extract the laser-material interaction sound. Audio equalization, bandpass filtering, and Harmonic-Percussive Source Separation (HPSS) algorithm are used to produce a cleaned laser-material interaction sound as the model's ground truth. Acoustic data was collected from experiments using different DED machines, materials, and varied process parameters to train the deep learning model. The proposed deep learning-assisted signal denoising strategy lays the groundwork for acoustic-based *in-situ* defect detection of the DED process.

2. Experimental setup

Acoustic data was collected from experiments using different DED machines, materials, and varied process parameters, as listed in Table 1. Three different types of DED equipment were used, two of which were robot-based, and one was CNC-based. Fig. 1 depicts the acoustic-based *in-situ* monitoring configurations for two distinct DED setup. The system depicted in Fig. 1(a) comprises a 6-axis industrial robot (KUKA KR90). On the robot arm's end-effector is a laser head with a coaxial powder feeding nozzle. The other robot-based DED system that uses an ABB IRB 4400 robot has a similar arrangement to the one shown in Fig. 1(a), hence it is not shown here. In Fig. 1(b), the laser head and powder feeding nozzle are installed within an enclosed CNC machine chamber. The acoustic signals for different DED processes were captured by a microphone (Xiris WeldMic) with a frequency response range of 50–20,000 Hz. The microphone sensor was positioned near the nozzle in both setups, and the sampling rate was set to 44,100 Hz.

3. Acoustic signal denoising

A deep learning-based end-to-end acoustic signal denoising framework is proposed to extract the laser-material interaction sound. The objective of the framework is to remove the environmental noise from the raw acoustic signal while minimizing undesired artefacts in the output signal. The details are explained as follows.

3.1. Deep learning-based end-to-end acoustic signal denoising framework

The overall architecture of the proposed acoustic signal denoising framework is depicted in Fig. 2. For the same denoising objective, two types of deep learning models are applied: a fully-connected regression deep neural network (F-DNN) [16,17] and a redundant convolutional encoder-decoder network (R-CED) [18]. Both networks were widely used for speech denoising and enhancement in the AI audio domain [19]. The raw acoustic signal obtained from the DED process, on the other hand, comprises a more complex noise source than the speech signal. This noise varies depending on the specific DED machine, material, and process settings. Therefore, as detailed in section 2, acoustic data were collected from experiments employing different DED machines, materials, and process parameters to provide a diverse dataset for training the deep learning model.

A three-step sound source extraction method was proposed to create a cleaned laser-material interaction sound as the ground truth label for the deep learning models, as illustrated in Fig. 2: (1) audio equalization, (2) bandpass filtering, and (3) Harmonic-Percussive Sources Separation (HPSS). The details of sound source extraction will be described in the subsequent Section 3.2.

After separating the laser-material interaction sound, the magnitude spectrum, which represents the energy concentration throughout time and frequency domains, is calculated using the short-time Fourier Transform (STFT) [20] on both the original and cleaned signals. The magnitude spectrums components are selected from the original and cleaned signals and are used as the inputs and targets of the deep learning models, respectively. Both networks seek to minimize the difference between the predicted and target magnitude spectrum. To transform the information back to time domain, the final denoised acoustic signal is obtained using inverse-STFT on the predicted magnitude spectrum.

3.2. Three-step sound source separation method

The Fast Fourier Transform (FFT) results for various sound source during the DED process are plotted in Fig. 3. Each sound source was recorded independently, with no other components of the process activated. The gas flow sound, for example, was recorded with only the gas switched on and the other process components turned off. Machine motion sound clearly contributes significantly to the low-frequency bands (0–1000 Hz), whilst other sources have a relatively modest impact on the overall acoustic output. However, all of the sound sources carry energy throughout the frequency domain, making the sound source separation difficult. To separate the laser-material interaction sound from the noisy environment, a three-step sound source separation method is presented as follows.

Firstly, raw acoustic signals were processed via audio equalization [21], which adjusts the magnitude of different frequency bands as illustrated in the block diagram in Fig. 4. The transfer function $H_{eq}(z)$ of the parallel audio equalizer can be expressed as:

Table 1
DED experiments for acoustic data collections.

Experiment number	DED machine	Powder Material	Laser Power (kW)	Speed (mm/min)	Powder flow rate (g/min)
1	ABB robot-based	Inconel 625	1.29	450	13.50
2	ABB robot-based	Inconel 625	2.4	1200	16.50
3	ABB robot-based	Bronze (CuNiAl)	0.8	900	3.13
4	KUKA robot-based	Maraging Steel	1.9	1200	10.50
5	CNC-based	Maraging Steel	0.9	900	2.09

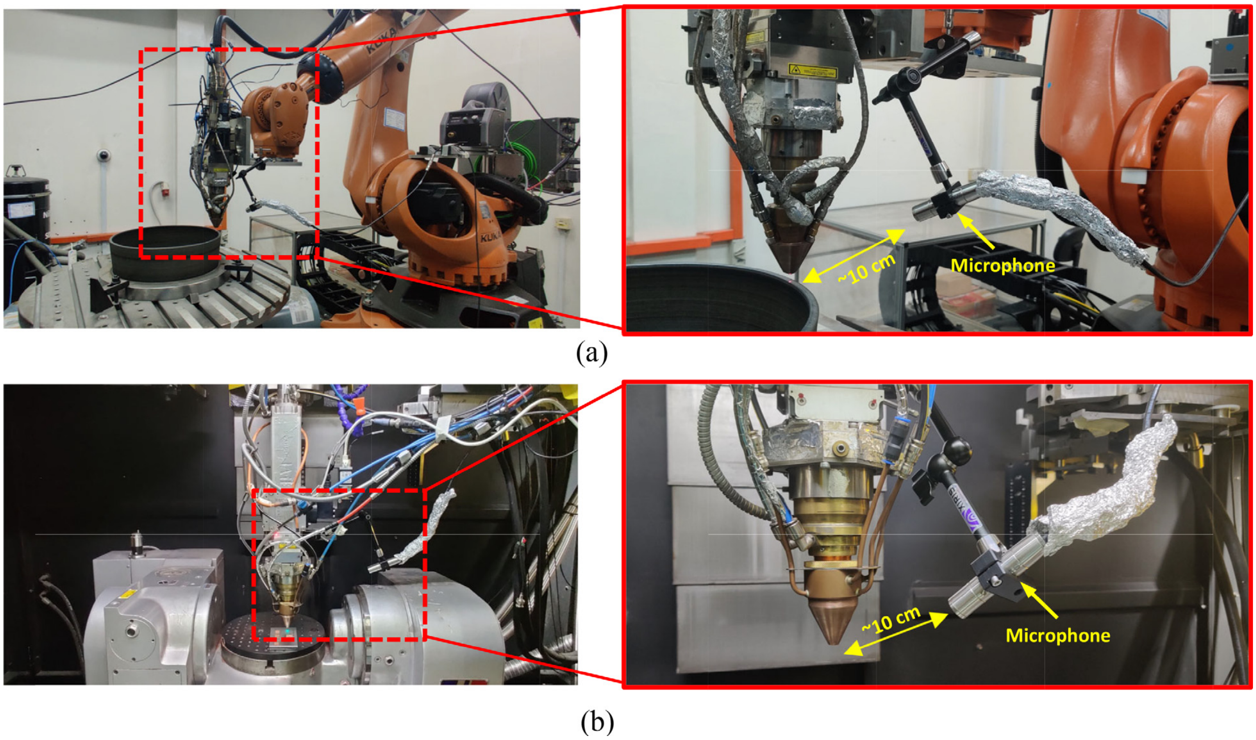

Fig. 1. Acoustic-based in-situ monitoring setup: (a) robot-based DED system, (b) CNC-based DED system.

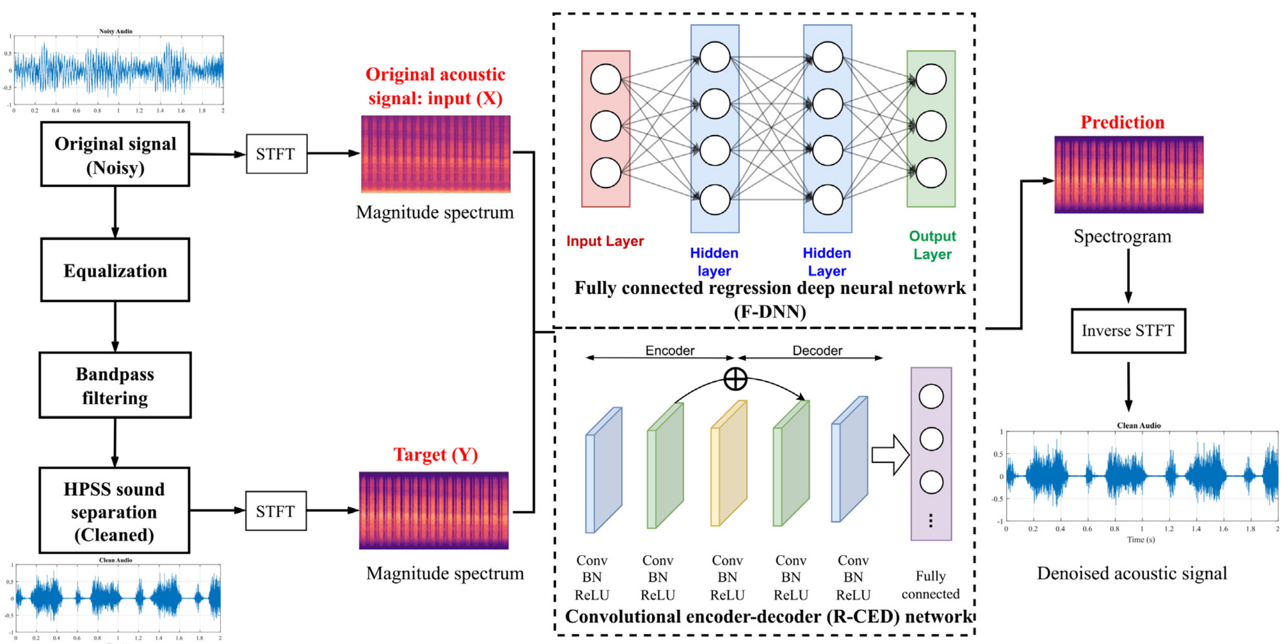

Fig. 2. Deep learning-based end-to-end denoising framework for DED acoustic-based monitoring.

$$H_{eq}(z) = \sum_{m}^{M} G_m H_m \quad (1)$$

where H_m represents the transfer function of each individual frequency band, and G_m represents the gains that control each bandwidth's magnitude. The gain is manually adjusted to decrease noise and enhance the sound of laser-material interaction. The magnitude was greatly reduced below 1000 Hz, where machine noise dominates. Gain values are determined through trial and error and must be fine-tuned for each unique experiment to meet a wide variety of machine and process conditions. The frequency response of the audio equalizer for Experiment 1 in Table 1 is illustrated in Fig. 5(a), where the magnitudes of frequency bands ranging from 1000 Hz to 20,000 Hz were increased, and the magnitudes of the remaining frequency bands were suppressed.

Secondly, a bandpass filter is used to reject high and low-frequency noise. As shown in Fig. 5(b), the filter passes frequencies between 3000 Hz and 2100 Hz while attenuating frequencies out-

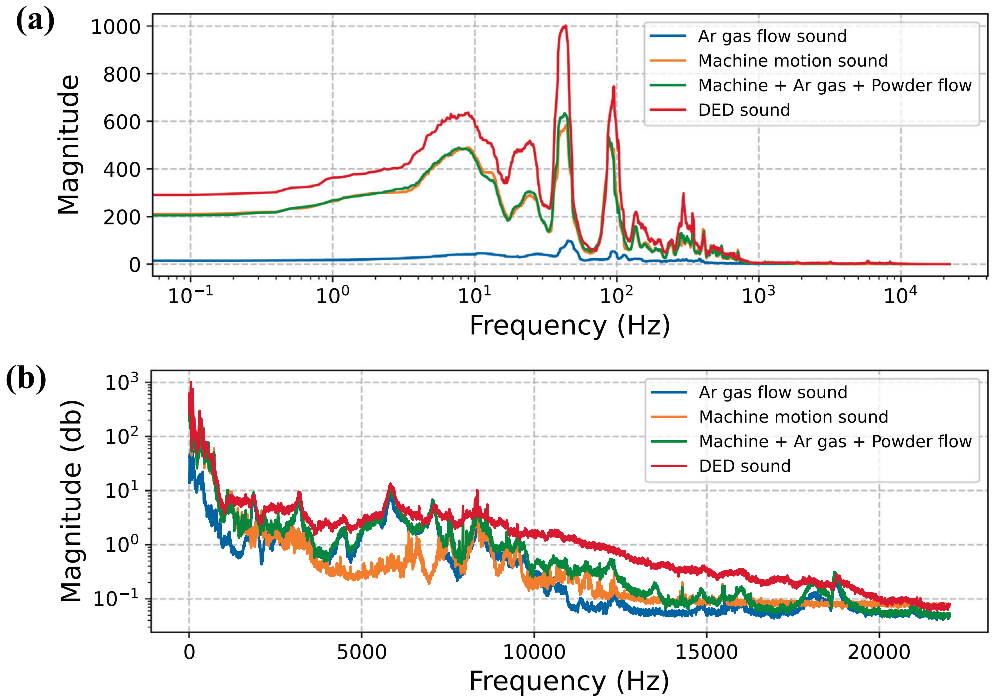

Fig. 3. Fast Fourier Transform (FFT) plots for different sound sources during DED process: (a) frequency in log scale, (b) magnitude in log scale.

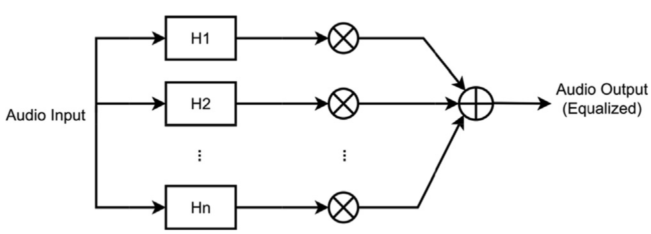

Fig. 4. Block diagram of audio equalizer in a parallel configuration.

side of this range. The rationale for this step is that, while the previous step's equalization significantly enhances the laser-material interaction sound, the noise components remain evident. More details on the effect of bandpass filtering will be shown in Section 4.

Thirdly, the final extraction is performed using the Harmonic-Percussive Sources Separation (HPSS) algorithm [22,23]. Since the noise produced by machine motion and gas flow has a frequency overlap with the laser-material interaction sound, the aforementioned techniques cannot completely eliminate the noise. The HPSS sound source separation method is especially effective for separating the harmonic and percussive components of monaural audio input. During our trial-and-error studies, we discovered that the laser-material interaction sound was the percussive component in the DED acoustic signal.

All the aforementioned steps are implemented using Python nussl [24] and librosa [25] library, and the deep learning models are implemented in MATLAB deep learning toolbox. The effect of each step will be illustrated in section 4.

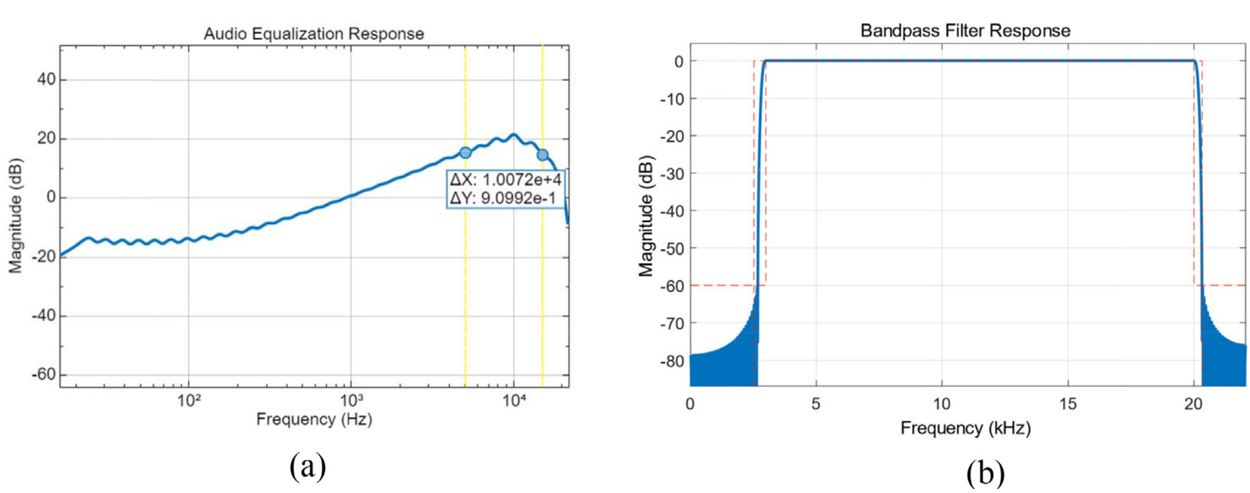

Fig. 5. Response of the audio equalizer and bandpass filter.

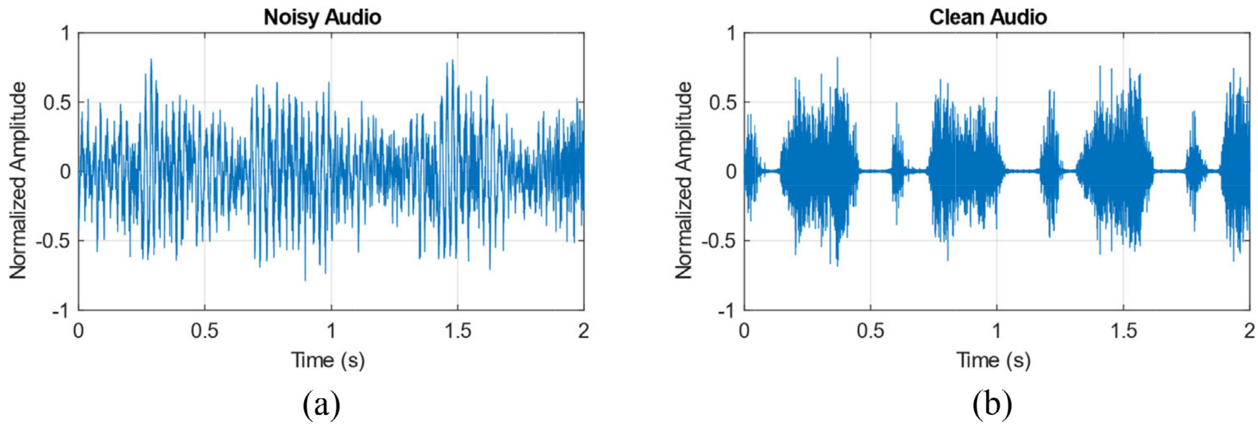

Fig. 6. Time-domain visualization of (a) original noisy acoustic signal and (b) final denoised signal.

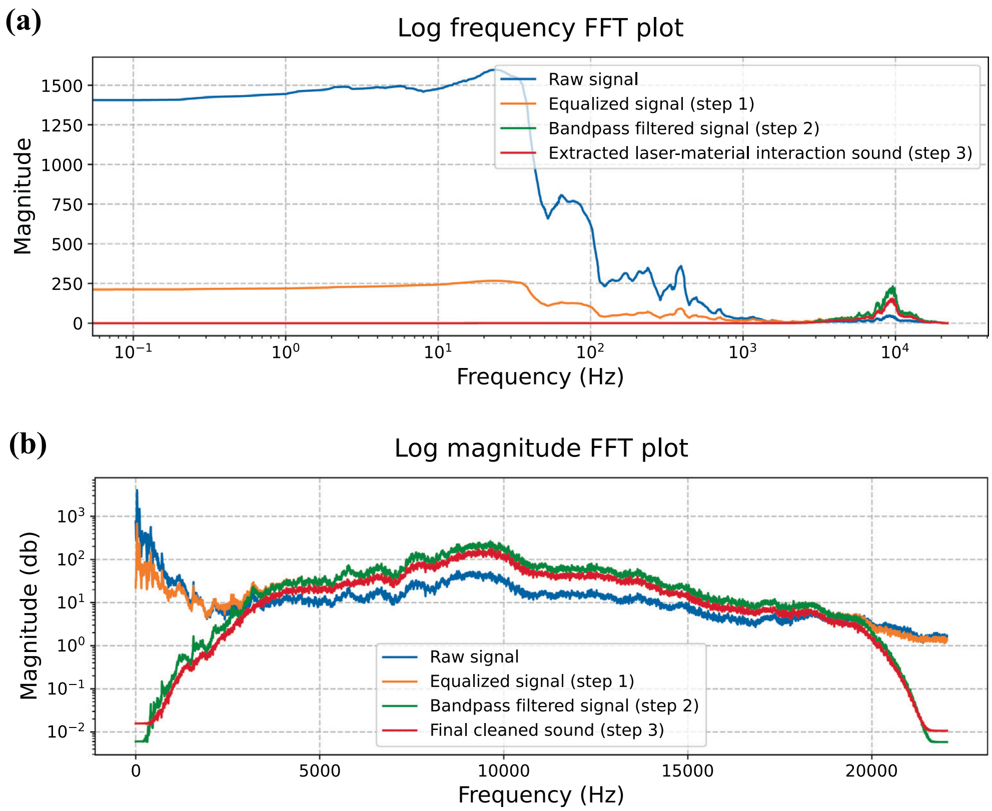

Fig. 7. Fast Fourier Transform (FFT) plots for each step of laser-material sound extraction: (a) frequency in log scale, (b) magnitude in log scale.

4. Result and discussion

Fig. 6 shows a 2-second time-domain slice of the original DED acoustic signal and the final cleaned laser-material interaction sound. The magnitude around zero in the cleaned sound indicates the "laser-off" period during the DED process. The FFT plots of each step of the proposed sound extraction method are visualized in Fig. 7. The audio equalizer suppressed the low-frequency noise while enhancing the volume from 1000 Hz to 20,000 Hz. Subsequently, the bandpass filter eliminates the sound outside the range of 3000 Hz and 2100 Hz. As a result, most of the machine sound and gas flow sound showed in Fig. 3 are removed or significantly reduced. In the final phase, the HPSS sound source separation isolates the percussive components of the acoustic signal that correlate to the laser-material interaction sound.

The three-step sound source separation method produces the target labels for the deep learning-based acoustic signal denoising framework. A total of 140 samples of acoustic signal components collected from different DED experiments were used to train the deep learning models. Each sample was truncated to 2 s, and 20% of the total data was used for validation. The models minimize the difference between the predicted and target magnitude spectra. The models were trained with NVIDIA GeForce RTX 3060 GPU. Both the R-CED network and the F-DNN show promise in mapping original noisy signals to extracted target signals. After 20 training epochs (with 557 iterations per epoch), the validation root means square error (RMSE) for R-CED and F-DNN networks is 1.1339 and 0.81539, respectively. The performance of the model still has significant room for improvement, which will be addressed in future research. Fig. 8 shows a screenshot of the R-

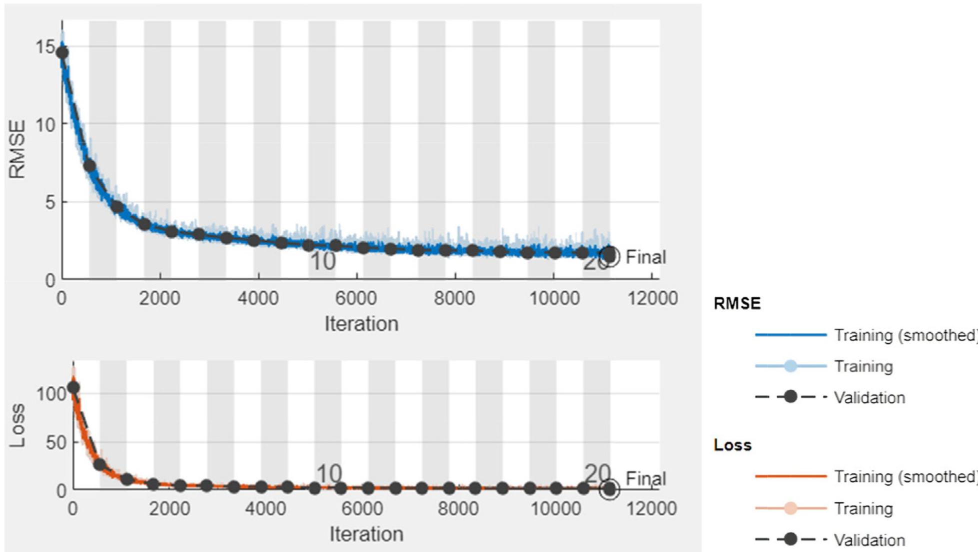

Fig. 8. A screenshot of the training progress for the R-CED network.

CED network's training progress, displaying the training process's convergence trend.

5. Conclusion

This paper presented a novel acoustic-based in-situ monitoring method for the DED process. A deep learning-based end-to-end acoustic signal denoising framework was developed to extract the laser-material interaction sound during the DED process. To produce the targets needed to train the deep learning model, a three-step sound source separation approach was developed: (1) audio equalizer was used to suppress the low-frequency band noise while increasing the volume of the laser-material interaction sound; (2) bandpass filtering was performed to eliminate the noise in high and low-frequency bands; (3) the HPSS separation algorithm then extracted the acoustic signal's percussive components, which correspond to the laser-material interaction sound. As a result, external noises such as machine movement, gas flow, and powder flow can be removed or significantly reduced. Two deep learning models were trained for the regression task: the *F-DNN* and *R-CED* networks. Both models showed feasibility in acoustic signal denoising, with the *F-DNN* network outperforming the *R-CED* with a lower RMSE. Future work includes improving the denoising network model performance and using the denoised acoustic signal to identify process anomalies and defects.

CRediT authorship contribution statement

Lequn Chen: Conceptualization, Methodology, Formal analysis, Software, Data curation, Validation, Investigation, Writing – original draft. **Xiling Yao:** Conceptualization, Methodology, Funding acquisition, Writing – review & editing. **Seung Ki Moon:** Supervision, Resources, Writing – review & editing, Project administration, Funding acquisition.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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