A Study On Plasma Cutting Machine's Nozzle Degradation Detection Method Based On Cutting Noise Analysis

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Abstract

Cutting of steel plates in shipbuilding is mainly performed by plasma cutting. In order to prevent the degradation of cutting quality, operators are forced to constantly monitor the deterioration of cutting torch nozzles. The nozzle replacement timing depends on the worker's experience, and no uniform standards have been established. In this study, a novel new technology has been developed to detect nozzle deterioration based on changes in cutting noise. A frequency scale that can scrutinize the ultrasonic frequency characteristics of cutting noise is proposed, and an acoustic feature based on the proposed ultrasonic frequency scale has been developed. The acoustic features of cutting noises generated from good-quality and deteriorated nozzles in straight cutting are imaged. Machine learning is performed using those images as teaching data to develop a classifier for the sound feature images. Optimization of the acoustic feature extraction process is carried out to adapt to the differences in the cutting noise characteristics for different cutting machines, and the relationship between the machine learning parameters and the classification accuracy is studied.

Keywords: Plasma cutting noise, Nozzle deterioration, Machine learning

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1. Introduction

Plasma cutting is primarily employed in the cutting process of steel materials for shipbuilding due to its superior productivity and expansive cutting capabilities. If cutting quality deteriorates below acceptable limits, the productivity declines due to reworks. A technology to prevent cutting quality deterioration must be developed. Consumable parts (electrodes and nozzles, shown in Fig. 1) must be replaced appropriately to maintain cutting quality. Operators are constantly monitoring the cutting state because plasma cutting machines cannot provide real-time feedback on the degradation of consumables. An in-situ monitoring method for consumable degradation needs to be developed.

The plasma cutting torch nozzle gradually deforms during cutting due to exposure to high-temperature and high-velocity plasma jets. This nozzle deformation should change the acoustic characteristics of the cutting noise.

Let the "deteriorated nozzle" be a nozzle that has deteriorated to the extent that rework is necessary to maintain cutting quality. Kawamoto et al.[1)] reported that the spectrum envelopes of cutting noise of good-quality and the deteriorated nozzles show a clear difference in the ultrasonic range around 30 kHz. The deterioration of consumables can be detected by analyzing this ultrasonic acoustic characteristic.

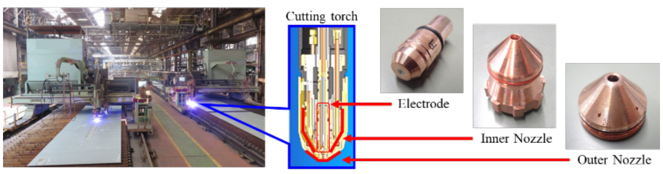


Fig. 1 Electrodes and nozzles used in plasma cutting machines.

In this study, a frequency scale that can scrutinize the ultrasonic frequency characteristics of cutting noise around 30 kHz is proposed, and an acoustic feature based on the proposed ultrasonic frequency scale is developed. The acoustic features of cutting noises generated from good-quality and deteriorated nozzles in straight cutting are imaged. Machine learning is performed using those images as teaching data to develop a CNN (Convolutional Neural Network) classifier for the sound feature images. The classifiers are developed for two plasma-cutting machines. Optimization of the acoustic feature extraction process is carried out to adapt to the differences in the cutting noise characteristics for different cutting machines, and the relationship between the machine learning parameters and the classification accuracy is studied.

2. Acoustic measurement and Features

2.1 Sampling Method of Cutting Noise

The cutting noises of two plasma cutting machines made by companies A and B (hereafter referred to as Machine-A and Machine-B) are analyzed. Recordings are made in each company's product testing laboratories and the shipyard cutting shops.

As shown in Fig. 2, three microphones (Zoom H2n digital voice recorders) are located 2,000 mm in front of the torch, 1,500 mm above the torch, and near the operation step. The workpieces are steel plates of 12 mm and 22 mm thickness coated by shop primer.

The cutting noise is recorded continuously at 96 kHz / 24 bit in MS-RAW mode. The noise from the end of the piercing to the end of the cutting is divided into frames of 1,000 msec. in length.

The consumables that deteriorate during cutting are the electrode and nozzle, and nozzles deteriorate faster than electrodes. In this study, cutting noises are recorded when a new nozzle (hereafter referred to as a “good-quality nozzle”) and a deteriorated nozzleis used.

2.2 Calculation Method of Acoustic Features

2.2.1 Ultrasonic Logistic Scale (ULS)

A scale transformation of frequency f (Hz) is generally performed in acoustic analysis. The transformation function for f is called a “scaling function” $T(f)$. $T(f)$ is chosen so that the gradient dT/df becomes larger in the frequency region where increased sensitivity to the acoustic characteristics is required. For example, in voice recognition, the Mel frequency is used, which can account for the human auditory characteristics that are higher at low frequencies and lower at high frequencies[2].

Kawamoto et al.[1] reported that changes in acoustic characteristics due to nozzle deterioration occur around 30 kHz. In this study, the logistic function Eq. (1) is adopted as the scale function so that a frequency scale that can scrutinize the ultrasonic characteristics around 30 kHz is defined. This scale is called the “Ultrasonic Logistic Scale (ULS)”.

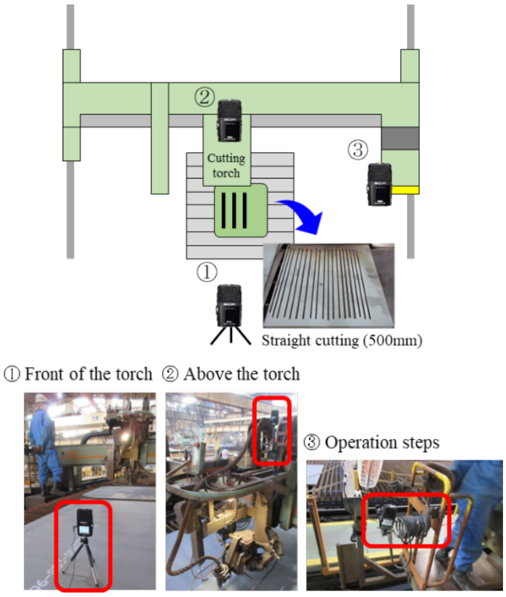


Fig. 2 Recorder installation positions relative to the cutting machine.

$$T_{\mathrm{logi}}(f) = \frac{K}{1 + b\exp(-c\,f)} \quad ;\ b = 2.0\times10^{4},\ c = 3.5\times10^{-4},\ K = 1000 \tag{1}$$

2.2.2 Ultrasonic Logistic-scaled Filter Bank (ULFB)

A filter bank arranged at equal intervals on the ULS is called the "Ultrasonic Logistic Filter Bank (ULFB)." Fig. 3 shows an ULFB of order 72.

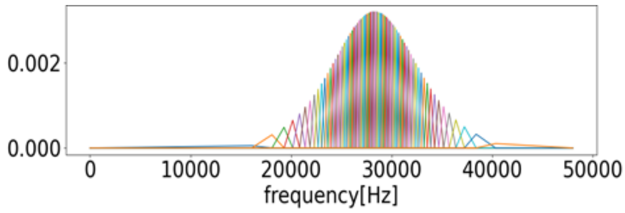
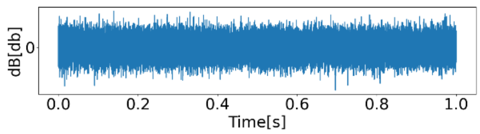


Fig. 3 Ultrasonic Logistic Filter Bank with an order of 72.

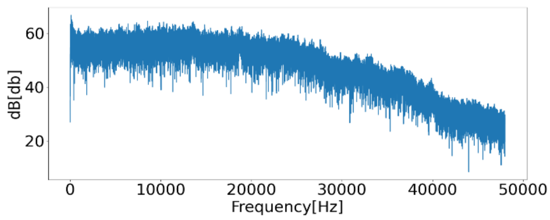
2.2.3 ULFB-treated Spectrum Envelope Stripe (USES)

Fig. 4 shows examples of sound waveform and log spectrum of cutting noise. The log spectrum contains significant noise-like signals. The noise-like signals represent the acoustic characteristics of the sound source (plasma turbulence in the cutting torch), while the spectrum envelope represents the acoustic characteristics of the articulatory filter (nozzle interior and orifice shape). The former is irrelevant to nozzle degradation, while the latter is the mechanism of nozzle degradation. Therefore, the spectrum envelope smoothed by the cepstrum method (liftering) is used to assess the deterioration.

For compressing the spectrum envelope, it is appropriate to compute the sub-band components of the ULFB focused on around 30 kHz. This compressed numerical sequence is called the "ULFB-filtered Spectrum Envelope (USE)", and its two-dimensional image (color stripes) are called the "ULFB-filtered Spectrum Envelope Stripe (USES)." In smoothing the spectrum, a liftering order of 140 is chosen in a trial-and-error manner. Fig. 5 (a) and (b) show examples of USES color maps of cutting noises for the cases with good-conditioned and deteriorated nozzles. The horizontal axis of Fig. 5(b) represents the frequency, and the critical frequency of 30 kHz is indicated by yellow lines. Fig. 5(b) indicates that as the nozzle deteriorates, the sub-band components around 30 kHz increase, and regions with large sub-band component fluctuations extend beyond 30 kHz into higher frequency ranges.

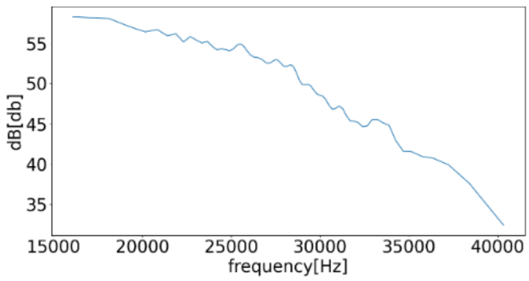


(a) Sound wavfoem

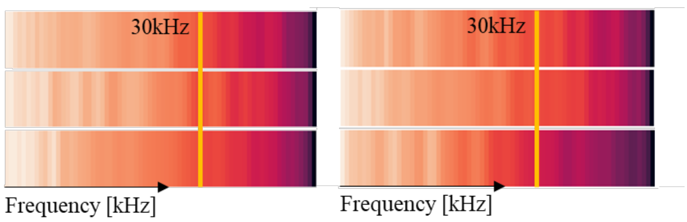


(b) Log spectrum

Fig. 4 Examples of sound waveform and log spectrum of cutting noise.



(a) ULFB-filtered spectrum envelop (USE)



(b) ULFB-filtered spectrum envelope stripe (USES)

Fig. 5 ULFB-filtered spectrum envelope (USE) and its color map (USES) (1st~72 th orders).

3. Detection of Nozzle Deterioration Using a CNN Image Classifier

A CNN image classifier is developed to detect nozzle deterioration. A pre-trained CNN, VGG16, is trained by fine-tuning the three layers on the output side.

3.1 Classification of Nozzle Deterioration Using USES

The teaching data is USES colormaps of the cutting noises recorded when cutting steel plates of 12 mm and 22 mm thickness in a straight line by Machine-A and Machine-B. Image augmentation (enlarging, rotating, etc.) is not performed because it loses specific properties of USES. The dataset used in the machine learning is shown in Table 1. Label 'N' represents a new (good-conditioned) nozzle, and 'D' represents a deteriorated nozzle. Figs. 6 and 7 show an example of the evolution of the classification performance of the developed image classifier for Machine-A with a thickness of 12 mm. The classification accuracy and loss for the chosen learning conditions are shown in Table 2. For Machine-A, the accuracy achieves 95% for cases with 12 mm and 22 mm thicknesses. For Machine-B with 22 mm thickness, the accuracy is only up to 80%.

Table 1 Dataset used for image classification.

Cutting Machine	thickness	train		validation		test	
		N	D	N	D	N	D
Machine A	12mm	32	77	15	38	15	38
	22mm	120	111	60	56	60	56
Machine B	12mm	177	260	88	130	88	130
	22mm	96	108	47	54	47	54

Table 2 Detection accuracy and loss for the chosen learning conditions.

Cutting Machine	thickness	epoch	steps per epoch	batch size	accuracy (%)	loss
Machine A	12mm	50	5	20	96.40	0.1747
	22mm	30	50	20	99.07	0.1504
Machine B	12mm	30	15	16	83.25	0.5294
	22mm	50	15	16	80.77	1.2879

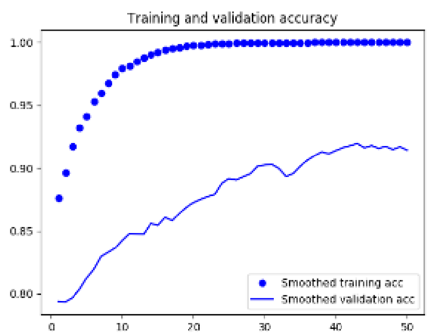


Fig. 6 Changes of the accuracy of USES image classification during the training (Machine A, t=12 mm)

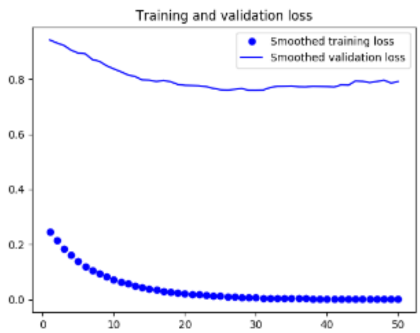


Fig. 7 Changes of the loss of USES image classification during the training (Machine A, t=12 mm).

3.2 Improving Detection Accuracy by Optimizing Parameters According to Acoustic Characteristics

The ULS parameters *b*, *c*, and *K* in Eq. (1) are chosen to maximize the detection sensitivity of spectral changes of Machine-A's noise. It is found that the spectral changes in Machine-B occur at higher frequencies than Machine-A. It is considered that the classification accuracy of Machine-B can be improved by changing those parameters.

Machine learning of Machine-B's cutting noise is repeated using three ULS parameter sets with different sensitivity bands shown in Table 3.

Table 4 shows the comparison of the classification accuracy for different ULS parameter sets. It is shown that the accuracy improves when the ULS parameters are chosen so that the sensitivity band extends to the high-frequency side. For case 3, accuracy as high as that of Machine-A is achieved for both 12 mm and 22 mm thicknesses. As shown in Table 1, machine learning in this study is performed on less than 1000 teaching data. Increasing the number of teaching data would further improve the accuracy.

Table 3 ULS parameters used for the machine learning of Machine-B's cutting noise.

condition	b	c	K	peak (kHz)	range (kHz)
used Sec.3	20,000	0.00035	1,000	28	16～40
1	200,000	0.00035	1,000	34	22～46
2	1,000	0.00025	1,000	28	11～43
3	5,000	0.00025	1,000	34	17～48

Table 4 Comparison of classification accuracy for different ULS parameter sets.

thickness	condition	epoch	steps per epoch	batch size	accuracy (%)	loss
12mm	1	50	15	16	84.27	0.5995
	2	30	15	16	85.68	0.4676
	3	40	50	16	89.75	1.1212
22mm	1	30	15	16	84.23	0.5503
	2	50	15	16	86.03	1.061
	3	40	50	16	93.08	0.5945

4. Conclusion

In this study, a frequency scale that can scrutinize the ultrasonic frequency characteristics of cutting noise around 30 kHz is proposed, and an acoustic feature based on the proposed scale is developed. The imaged acoustic features (ULFB-treated Spectrum Envelope's Stripe, USES) of cutting noises generated from good-quality and deteriorated nozzles in straight cutting are generated, and machine learning of USES is performed to develop a CNN classifier for the sound feature images. The findings are summarized as follows:

1 The USES can scrutinize the change in the acoustic characteristics around 30kHz due to the nozzle deterioration.

2 By training the image classifier VGG16 with USES obtained from good-conditioned and deteriorated nozzles, the nozzle degradation level is classified with practical accuracy (>95%) for the cases with Machine A and plate thicknesses of 12mm and 22mm.

3 For Machine B, adjusting the scale function parameters to enhance the acoustic features in the 30 kHz and above range improves the classification accuracy to around 90%. Optimizing the USES generation process and increasing the number of sample data would further improve classification accuracy.

Acknowledgements

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