# **Research on Machine Learning Model for Detecting Ultrasonic Signals**

Kosei OZEKI<sup>†</sup>, Nonmember, Naofumi AOKI<sup>†</sup>, Member, Yoshinori DOBASHI<sup>†</sup>, Member

## 1. Introduction

Sonic communication [1] enables communication in environments where radio waves cannot reach. However, it is susceptible to errors caused by noise and the Doppler effect. In this paper, we simulate a sound signal degraded by white noise and frequency shift. We design a classifier using machine learning to extract information from this sound signal and demonstrate its effectiveness.

## 2. Proposed technique

In this paper, we design a communication system using FSK modulation to embed sound signals in the inaudible range of 18kHz to 20kHz. The length of one sound signal (1 symbol) is set to 41.66ms, and by adjusting the guard interval between symbols, we achieve a communication speed of 24bps. The sound signals are organized based on a hopping pattern consisting of 400 symbols. Utilizing the spectrogram representation, which expresses time and frequency information as a 2-dimensional image, each sound signal can be expressed as shown in Figure 1 (a), and the hopping patterns in that spectrogram can be expressed as shown in Figure 1(b). The proposed classifier is designed to obtain the hopping pattern of sound signals including white noise and frequency shift using three machine learning models (CNN, RNN, and CRNN). The structure of each model is shown in Table 1. For training, ADAM optimizer is used, loss function is binary cross entropy, the learning rate is 0.001, and the number of training epochs is 30.

The classifier is trained spectrograms and hopping patterns of sound signals that include white noise ranging from -10dB to 50dB and frequency shifts within  $\pm 30$ Hz. For each, 80,000 data are prepared for training, and 20,000 data are reserved for validation.

In the evaluation experiment, 1,000 evaluation data were prepared for each SNR ranging from -10dB to 40dB. The evaluation results are shown in Figure 2. From the results, it can be observed that the classifier using CRNN achieved the highest recognition rate. The accuracy was over 90% when the SNR was over 3dB. When noise is low, high discrimination accuracy is obtained regardless of the frequency shift. On the other hand, when the noise is high, the classifier finds it difficult to discriminate signals. Future work is needed to evaluate the classifier against impulsive noise for practical use.

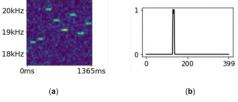


Fig. 1 Input spectrograms and labels used for learning.

Table 1 Structure and parameters of the machine learning mo	de	1
---	----	---

	CNN	RNN	CRNN	
input size	$64 \times 64 \times 1$			
# CNN layers	3	-	3	
pool size	2×2	-	$1 \times 4$	
# RNN layers	-	2	2	
# FNN layers	1	1	1	
# feature maps	32	-	32	
# hidden units	-	32	32	
# dense units		64		
# Parameters	176,336	325,840	338,896	

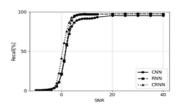


Fig. 2 Accuracy of machine learning models per SNR

#### 3. Conclusions

In this study, we designed a classifier using machine learning models based on CNN, RNN, and CRNN to detect hopping patterns from spectrograms of simulated sound signals. The results showed machine learning model using CRNN has demonstrated effectiveness against frequency shifts. In the future, we will work on evaluating the performance of the model with recorded data.

#### References

 K.Ozeki, et al, "Acoustic event detection of ultrasonic signals using CNN," IEICE2021, p2-7,2021.

<sup>&</sup>lt;sup>†</sup>The author is with Graduate School of Information Science and Technology, Hokkaido University, Sapporo, 060-0814 Japan