Abstract—Sounds recorded with smartphones or IoT devices often have partially unreliable observations caused by clipping, wind noise, and completely missing parts due to microphone failure and packet loss in data transmission over the network. In this paper, we investigate the impact of the partially missing channels on the performance of acoustic scene classification using multichannel audio recordings, especially for a distributed microphone array. Missing observations cause not only losses of time-frequency and spatial information on sound sources but also a mismatch between a trained model and evaluation data. We thus investigate how a missing channel affects the performance of acoustic scene classification in detail. We also propose simple data augmentation methods for scene classification using multichannel observations with partially missing channels and evaluate the scene classification performance using the data augmentation methods.

Index Terms—Acoustic scene classification, multichannel processing, missing observation, data augmentation

I. INTRODUCTION

Acoustic scene classification (ASC), which classifies sound recordings into the predefined class such as recording environments, places, and daily activities, is one of the core search problems in environmental sound analysis [1]–[3]. ASC has significant potential for various applications such as monitoring infants/elderly people [4], automatic surveillance [5], automatic life-logging [6], and media retrieval [7].

Many methods for ASC utilizing spectral information have been proposed. For instance, Eronen et al. [8] and Mesaros et al. [9] have proposed methods based on mel-frequency cepstral coefficients (MFCCs) and Gaussian mixture models (GMMs). Valenti et al. [10], Han et al. [11], and Jallet et al. [12] have proposed methods using mel-spectrograms and a convolutional neural network (CNN). Liping et al. [13], Tanabe et al. [14], and Raveh and Amar [15] have proposed Xeption-based, VGG-based, and ResNet-based ASC methods, respectively.

More recently, environmental sound analysis utilizing spatial information, which is extracted from time differences or sound power ratios between channels, has also been studied [14], [16]–[20]. Conventional microphone array processing requires that microphones are synchronized between channels and/or microphone locations or array geometry is known. However, spatial information based on accurate time differences or sound power ratios between channels cannot be extracted using a combination of unsynchronized distributed microphones such as smartphones, IoT devices, and surveillance cameras. To utilize unsynchronized distributed microphones whose locations or array geometry is unknown for multichannel ASC, Kürby et al. [21] have proposed a method based on the late fusion of scene classification results obtained with each microphone. Many conventional methods for multichannel ASC also apply this strategy [22], [23]. Imoto et al. have proposed ASC methods using the spatial cepstrum and graph cepstrum that can be applied under an unsynchronized condition [18], [20].

On the other hand, sounds recorded with smartphones or IoT devices often have missing parts caused by microphone failure, packet loss in data transmission over the network, or unreliable observations caused by clipping and wind noise. To analyze acoustic scenes from intermittently missing observations with a single-channel microphone, Imoto and Ono have proposed a method of simultaneously analyzing acoustic scenes and estimating missing observations [24]. However, the conventional method is not for multichannel audio recordings, and the impact of partially missing channels on the ASC performance using multichannel audio recordings has not been investigated in the conventional works.

In this paper, we thus investigate the impact of partially missing channels on the performance of multichannel ASC, especially for the distributed microphone array. In machine-learning-based multichannel ASC, missing channels cause not only losses of time-frequency and spatial information on sound sources but also a mismatch between a trained model and evaluation data. Therefore, to realize a robust ASC system, it is important to investigate how a missing channel affects the ASC performance. We then apply simple data augmentation methods for multichannel ASC with partially missing channels and evaluate the scene classification performance using the data augmentation methods.

The remainder of this paper is organized as follows. In section 2, we discuss conventional acoustic scene classification using multichannel observation. In section 3, we introduce three simple data augmentation methods for multichannel ASC with missing channels. In section 4, we report the results of experiments carried out to evaluate the performance of ASC with partially missing channels and the impact of missing channels on the ASC performance. Finally, we conclude this paper in section 5.
II. Conventional Methods for Scene Classification

Let us consider a model \( f \) and model parameter \( \theta \). The purpose of ASC is to estimate an acoustic scene label \( \hat{z} \) in an evaluated sound as

\[
\hat{z} = \arg \max_z f(X, \theta),
\]

(1)

where \( z \) and \( X \in \mathbb{R}^{F \times T \times C} \) are the acoustic scene class and acoustic feature, respectively. \( F \), \( T \), and \( C \) are the numbers of frequency bins, time frames, and channels, respectively. The model parameter \( \theta \) is preliminarily determined using the training dataset \( D = \{(X_1, z_1), \ldots, (X_l, z_l), \ldots, (X_L, z_L)\} \). Here, \( X_l \) is the acoustic feature of the \( l \)th sound clip and \( z_l \) indicates an acoustic scene label in the \( l \)th sound clip. For the acoustic feature \( X_l \), the mel-band energy and MFCCs are often used. As the model \( f \), GMMs, a CNN, a ResNet-based, or a VGG-based method has often been applied. In the neural-network-based methods, the model parameter \( \theta \) is estimated using the softmax cross-entropy loss function and the backpropagation technique.

Most conventional methods assume that there is no missing channel in a multichannel observation. However, in the scenario of a distributed microphone array, we may have partially missing channels caused by microphone failure, in which some acoustic feature \( X_c \) in the \( c \)th channel cannot be utilized in the evaluation data.

III. Data Augmentation for Multichannel Scene Classification

In this work, we apply three data augmentation methods for multichannel scene classification with partially missing channels. These data augmentation methods are reasonably simple to implement and enable us to investigate how partially missing channels affect the ASC performance.

A. Channel Mask

The data missing in the evaluation stage causes a mismatch between the trained model and evaluation data. To avoid this mismatch, we apply simple binary masking throughout the input time-frequency features for the random channels in the model training stage as follows:

\[
X_{l,c} = O,
\]

(2)

where \( X_{l,c} \) is the acoustic feature of the \( l \)th sound clip in the \( c \)th channel. \( O \) is the zero matrix when the acoustic feature is the linear spectrum, whereas it is the matrix that has negative infinity values in its element when the acoustic feature is the log spectrum.

B. Channel Overwrite and Random Copy

When applying channel mask, a large gap may remain between the unmasked channel in the training data and the missing channel in the evaluation data. To bridge this gap, we apply a data augmentation method using channel overwrite in the model training stage and a random copy in the evaluation stage. Channel overwrite mandatorily overwrites the time-frequency features between channels in model training as follows:

\[
X_{l,c} = X_{l,c'}.
\]

(3)

In the evaluation stage, we randomly copy the acoustic features from non-missing channels to missing channels.

C. Channel Swap and Random Copy

Channel mask and channel overwrite lose time-frequency information since we discard time-frequency features in the
training stage. To train the scene classification model without wasting time-frequency information, we apply a data augmentation method using channel swap. Channel swap simply swaps the time-frequency features between channels in model training as follows:

\[
\begin{align*}
X_{t,c} &= X_{t,c'} \\
X_{t,c'} &= X_{t,c}.
\end{align*}
\]

In the evaluation stage, we randomly copy the acoustic features from non-missing channels to missing channels as with the data augmentation in channel overwrite.

IV. EXPERIMENTS

A. Experimental Conditions

We evaluate the impact of a missing channel on the performance of scene classification using various data augmentation methods. To evaluate the performance, we use the development dataset of DCASE2018 Challenge Task 5 [25], which is a derivative of the SINS dataset [26]. We construct each 10 s audio segment with sounds recorded by four microphone arrays; that is, each audio segment contains 16 channels. As shown in Table I, the dataset contains 18,246 audio segments, and we split them into the same 4-fold cross-validation setup as in Table I, the dataset contains 18,246 audio segments, and we split them into the same 4-fold cross-validation setup as in DCASE2018 Challenge Task 5.

For the acoustic features, we use the 40-dimensional log mel-band energy, which has a frame length of 40 ms with hop size of a 20 ms. In this paper, we regard the missing channels as silent with zeros filled in the time domain. As the classification model, we apply the same network proposed by Inoue et al. [22], which achieved the best score in DCASE2018 Challenge Task 5, except for the input channel size of the network. The detailed network structure is shown in Table II. We utilize the RAdam optimizer [27] with a learning rate of 0.001. For each method, we conduct the evaluation experiment 16 (random combinations of missing channels) × 4 (fold) times.

B. Experimental Results

1) Impact of Missing Channel on Classification Performance: We evaluate the performance degradation caused by missing channels in the evaluation data. Table III shows the scene classification performance in terms of micro- and macro-Fscore. The result shows that the missing channels cause severe performance degradation in multichannel ASC.

To investigate how the missing channels affect the ASC performance, we also evaluate the ASC performance with the same channels missing in the training and evaluation datasets. Table IV shows the scene classification performance in terms of micro- and macro-Fscore with the proposed data augmentation methods. The results show that the three data augmentation methods achieve reasonable performances.

2) Evaluation of Data Augmentation Technique for Multichannel ASC: We next evaluate the ASC performance with the proposed data augmentation methods. In this experiment, we randomly select a number of channels from 0 to 8 for data augmentation in each iteration of model training. Tables V and VI show the scene classification performance in terms of micro- and macro-Fscore with the proposed data augmentation methods. The results show that the three data augmentation methods achieve reasonable performances. In particular, channel overwrite and channel swap achieve comparable ASC performance to the result without missing channels. Comparing these results with Table IV indicates that

### Table V

|                | w/o missing | 1ch missing | 2ch missing | 4ch missing | 8ch missing | 12ch missing |
|----------------|-------------|-------------|-------------|-------------|-------------|--------------|
| w/o augmentation | 96.80%      | 85.50%      | 74.88%      | 60.93%      | 38.63%      | 17.67%       |
| Channel mask    | 95.54%      | 95.59%      | 95.45%      | 94.85%      | 92.47%      | 76.01%       |
| Channel overwrite + Random copy | 95.81%      | 95.78%      | 95.68%      | 95.36%      | 93.91%      | 91.43%       |
| Channel swap + Random copy | 95.85%      | 95.82%      | 95.72%      | 95.39%      | 94.06%      | 91.46%       |

### Table VI

|                | w/o missing | 1ch missing | 2ch missing | 4ch missing | 8ch missing | 12ch missing |
|----------------|-------------|-------------|-------------|-------------|-------------|--------------|
| w/o augmentation | 93.60%      | 65.90%      | 45.66%      | 31.44%      | 13.34%      | 13.98%       |
| Channel mask    | 90.63%      | 90.76%      | 90.42%      | 88.81%      | 84.28%      | 51.99%       |
| Channel overwrite + Random copy | 90.75%      | 90.75%      | 90.53%      | 90.06%      | 88.21%      | 83.98%       |
| Channel swap + Random copy | 90.74%      | 90.75%      | 90.54%      | 90.13%      | 88.27%      | 84.07%       |
channel overwrite and channel swap can almost completely avoid the mismatch between the trained model and evaluation data.

3) Detailed Scene Classification Performance: Figs. 1–3 show the detailed scene classification performance using no data augmentation method and channel swap with four channels missing. The results show that most of the audio segments are predicted as “other.” On the other hand, the classification result using channel swap achieves comparable performance to that without missing channels. From these results, we conclude that, in multichannel ASC, partially missing channels may cause a severe degradation of the ASC performance, and avoiding the mismatch between the trained model and evaluation data is important to achieve a robust ASC system in a realistic situation.

V. CONCLUSION

In this paper, we investigated the impact of partially missing channels on the ASC performance using multichannel audio recordings obtained using a distributed microphone array. We also proposed three data augmentation methods for multichannel ASC: channel mask, channel overwrite, and channel swap. The experimental results showed that, in multichannel ASC, the mismatch between the trained model and evaluation data is a much more severe problem than missing spectral and spatial information. To avoid this negative impact on the ASC performance, the data augmentation based on channel overwrite and channel swap is effective and can avoid the performance degradation caused by the model mismatch.

ACKNOWLEDGMENT

This work was supported by JSPS KAKENHI Grant Number JP20H00613, JP19K20304, and KDDI Foundation.

REFERENCES

[1] T. Virtanen, M. Plumbley, and D. Ellis, Eds., Computational Analysis of Sound Scenes and Events. Springer, 2017.
[2] K. Imoto, “Introduction to acoustic event and scene analysis,” Acoustical Science and Technology, vol. 39, no. 3, pp. 182–188, 2018.
[3] T. Heittola, A. Mesaros, and T. Virtanen, “Acoustic scene classification in DCASE 2020 challenge: Generalization across devices and low complexity solutions,” Proc. Workshop on Detection and Classification of Acoustic Scenes and Events (DCASE), pp. 56–60, 2020.
[4] A. Mesaros, T. Heittola, A. Diment, B. Elizalde, A. S. E. Vincent, B. Raj, and T. Virtanen, “DCASE 2017 challenge setup: Tasks, datasets and baseline system,” Proc. Detection and Classification of Acoustic Scenes and Events Workshop (DCASE), pp. 85–92, 2017.
[5] S. Ntalampiras, I. Potamitis, and N. Fakotakis, “On acoustic surveillance of hazardous situations,” Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 165–168, 2009.
[6] K. Imoto and S. Shimauchi, “Acoustic scene analysis based on hierarchical generative model of acoustic event sequence,” IEICE Trans. Inf. Syst., vol. E99-D, no. 10, pp. 2539–2549, 2016.
[7] Q. Jin, P. F. Schulam, S. Rawat, S. Burger, D. Ding, and F. Metze, “Event-based video retrieval using audio,” Proc. INTERSPEECH, pp. 2085–2088, 2012.
[8] A. Eronen, V. T. Peltonen, J. T. Tuomi, A. P. Klapuri, S. Fagerlund, T. Sorsa, G. Lorho, and J. Huopaniemi, “Audio-based context recognition,” IEEE Trans. Audio Speech Lang. Process., vol. 14, no. 1, pp. 321–329, 2006.
[9] A. Mesaros, T. Heittola, A. Eronen, and T. Virtanen, “Accounting for missing channels in evaluation data,” Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 165–168, 2009.
[10] M. Valenti, S. Squartini, A. Diment, G. Parascandolo, and T. Virtanen, “A convolutional neural network approach for acoustic scene classification,” 2017 International Joint Conference on Neural Networks (IJCNN), pp. 1547–1554, 2017.
[11] Y. Han, J. Park, and K. Lee, “Convolutional neural networks with binaural representations and background subtraction for acoustic scene classification,” Proc. Detection and Classification of Acoustic Scenes and Events Workshop (DCASE), pp. 1–5, 2017.
dereverberation, blind source separation, data augmentation, and model ensembling,” Tech. Rep. DCASE Challenge Task 5, 2018.
[15] A. Raveh and A. Amar, “Multi-channel audio classification with neural network using scattering transform,” Tech. Rep. DCASE Challenge Task 5, 2018.
[16] H. Kwon, H. Krishnamoorthi, V. Berisha, and A. Spanias, “A sensor network for real-time acoustic scene analysis.” Proc. IEEE International Symposium on Circuits and Systems, pp. 169–172, 2009.
[17] P. Giannoulis, A. Brutti, M. Matassoni, A. Abad, A. Katsamanis, M. Matos, G. Potamianos, and P. Maragos, “Multi-room speech activity detection using a distributed microphone network in domestic environments,” Proc. 23rd European Signal Processing Conference (EUSIPCO), pp. 1271–1275, 2015.
[18] K. Imoto and N. Ono, “Spatial cepstrum as a spatial feature using distributed microphone array for acoustic scene analysis,” IEEE/ACM Trans. Audio Speech Lang. Process., vol. 25, no. 6, pp. 1335–1343, 2017.
[19] K. Nakadai and D. R. Onishi, “Partially-shared convolutional neural network for classification of multi-channel recorded audio signals,” Tech. Rep. DCASE Challenge, 2018.
[20] K. Imoto, “Graph cepstrum: Spatial feature extracted from partially connected microphones,” IEICE Trans. Inf. Syst., vol. E103-D, no. 03, pp. 631–638, 2020.
[21] J. Kürby, R. Grzeszick, A. Plinge, and G. A. Fink, “Bag-of-features acoustic event detection for sensor networks,” Proc. Detection and Classification of Acoustic Scenes and Events Workshop (DCASE), pp. 55–59, 2016.
[22] T. Inoue, P. Vinayavekhin, S. Wang, D. Wood, N. Greco, and R. Tachibana, “Domestic activities classification based on CNN using shuffling and mixing data augmentation,” Tech. Rep. DCASE Challenge Task 5, 2018.
[23] H. Liu, F. Wang, X. Liu, and D. Guo, “An ensemble system for domestic activity recognition,” Tech. Rep. DCASE Challenge Task 5, 2018.
[24] K. Imoto and N. Ono, “Acoustic topic model for scene analysis with intermittently missing observations,” IEEE/ACM Trans. Audio Speech Lang. Process., vol. 27, no. 2, pp. 367–382, 2019.
[25] G. Dekkers, L. Vuegen, T. Waterschoot, B. Vanrumste, M. Verhelst, and P. Karsmakers, “DCASE 2018 challenge - task 5: Monitoring of domestic activities based on multi-channel acoustics.” Tech. Rep. DCASE Challenge Task 5, 2018.
[26] G. Dekkers, S. Lauwereins, B. Thoen, M. W. Adhana, H. Brouckx, T. Waterschoot, B. Vanrumste, M. Verhelst, and P. Karsmakers, “The SINS database for detection of daily activities in a home environment using an acoustic sensor network,” Proc. Workshop on Detection and Classification of Acoustic Scenes and Events (DCASE), pp. 32–36, 2017.
[27] L. Liu, H. Jiang, P. He, W. Chen, X. Liu, J. Gao, and J. Han, “On the variance of the adaptive learning rate and beyond,” Proc. International Conference on Learning Representations (ICLR), pp. 1–13, 2020.