TECHNICAL REPORT

Identification of jet aircraft model based on frequency characteristics of noise by convolutional neural network

Makoto Morinaga^{1,*}, Junichi Mori¹, Takanori Matsui²,
Yasuaki Kawase³ and Kazuyuki Hanaka³

¹*Defense Facilities Environment Improvement Association,
3-41-8 Shiba, Minato-ku, Tokyo, 105-0014 Japan*

²*Osaka University,
2-1 Yamadaoka, Suita, 565-0871 Japan*

³*Narita International Airport Promotion Foundation,
76 Amazutsumi, Kayamashinden, Shibayama, Sanbu, Chiba, 289-1601 Japan*

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Abstract: We have been developing an aircraft model identification system that uses a convolutional neural network (CNN). The assumption is that this identification system would be used to estimate the number of flights to create noise maps. In our previous study, we used the CNN model to classify five aircraft comprising three rotorcraft, one turboprop, and one jet aircraft, and the accuracy reached 99%. In the present study, to examine whether this method is also effective for identifying the sound sources of jet aircraft, we conducted two case studies using frequency characteristics of aircraft noise obtained from field measurements around Osaka International Airport and Narita International Airport. Targeting 7 and 18 types of sound source at Osaka and Narita, respectively, an identification rate of 98% was obtained in both cases. This suggests that the present system can estimate the number of jet aircraft flights for each engine type or each aircraft model with very high accuracy.

Keywords: Aircraft noise, Noise source identification, Convolutional neural network, Residual network, Machine learning

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1. INTRODUCTION

1.1. Motivation

To examine the priority of noise policies, it is necessary to understand the actual situation of noise effects such as annoyance, sleep disturbance, and health effects. To that end, it is necessary to develop exposure–response relationships by collecting response data derived from social and epidemiological surveys and estimating long-term exposure by creating noise maps [1]. In particular, there is widespread exposure to aircraft noise, but field measurements are limited in their ability to estimate the amount of exposure to that noise.

Generally, to estimate representative long-term noise exposure, year-averaged noise maps are created using predictive models based on the annual average number of flights of each aircraft model. When creating a noise map in cooperation with government or airport companies, the numbers of flights can be derived from actual operational

data. In other cases, it is necessary to estimate the number of flights from airport timetables and/or automatic dependent surveillance–broadcast (ADS-B) data [2]. However, timetables are not necessarily consistent with actual operational outcomes. Also, estimation by ADS-B is limited because not all aircraft transmit the required mode-S transponder signal.

1.2. Previous Studies

For this reason, we have been developing an aircraft model identification system that uses machine learning, the aim being to use the frequency characteristics of aircraft noise to classify automatically the sound sources of aircraft noise events according to the aircraft model. In previous studies, Morinaga *et al.* [3] and Matsui and Morinaga [4] applied the machine-learning techniques of the random forest algorithm [5] and support vector machines [6] to a vast amount of measurement data. In those studies, the learning data were the one-third octave band levels when the A-weighted sound pressure level reached maximum and 1 s before and after that time. Identification was

*e-mail: mrngmkt@gmail.com

conducted for three types of jet fighter aircraft model, and the identification accuracy was approximately 90%. In another study, Quaranta and Dimino [7] used a neural network to classify four types of sound source consisting of takeoff and landing sounds of two turboprop aircraft and one jet aircraft; they reported a total identification accuracy of 95%. However, using the same method, Quaranta and Dimino [8] reported that the accuracy rate decreased to no more than 90% when classifying nine sound sources comprising takeoff and landing jet aircraft sounds. These results suggest that, unlike a turboprop aircraft whose sound source includes a pure tone component, it is difficult to identify the model of a jet aircraft whose noise components are broadband in range. They also suggest that the accuracy rate decreases with more aircraft models to be classified. Ruiz *et al.* [9] and Sanchez-Perez *et al.* [10,11] reported the results of using a neural network to classify 13 types of jet aircraft, the identification rate being 85–90%. As such, the accuracy of aircraft model identification in previous studies targeting jet aircraft is approximately 90%.

In our aforementioned previous studies [3,4], the time range of the input data used for learning was narrow because the calculation time was limited. This led to the problem that there was very little information about the features of the aircraft noise. However, machine-learning technology has advanced considerably since then. In particular, deep neural networks are attracting attention as a breakthrough technique for reducing the enormous computational cost of analysis processes, and Nakajima *et al.* [12] have used such networks to recognize the sources of environmental noise. In our another previous study, Mori *et al.* [13] used convolutional neural network (CNN) to classify five aircraft types comprising three rotorcraft, one turboprop, and one jet aircraft. As learning data, we used the one-third octave band levels in the time range of 180 s centered at the time of maximum A-weighted sound pressure level ($L_{A,Smax}$) in each aircraft noise event, and the identification accuracy reached 99%.

1.3. Purpose

Although our previous study [13] was targeted mainly at the sound sources of rotorcraft, the classification of rotorcraft noise is relatively easy because rotorcraft sound has characteristic frequency components with a dominant tonal sound, as suggested by Quaranta and Dimino [7,8]. In the present paper, we show the results of identifying jet aircraft models in two case studies conducted near Narita International Airport and Osaka International Airport. The purpose of this paper is to examine the effectiveness of the CNN-based identification method with field measurement data of jet aircraft noise as the learning data.

2. CASE STUDY 1: LANDING NOISE MEASURED NEAR OSAKA INTERNATIONAL AIRPORT

2.1. CNN Input Data

A CNN automatically recognizes features of the input data by repeatedly learning from information about the correct answers. To obtain the input data for the machine learning in the present case, continuously recorded aircraft noise and information about the aircraft model for each recorded noise event were acquired simultaneously. The field measurements were conducted from December 2017 to February 2018, a total of 69 days, at one location near a flight path of Osaka International Airport in Japan. The recording site was located 5 km south of the end of the airport runway. Because more than 95% of the airport operation is northward throughout the year, all the data obtained in these measurements were landing sounds. The landing sounds were recorded on a computer through a sound level meter (Rion; NL-52). The Z frequency weighting was used, and the aircraft model for each recorded aircraft noise event was identified from the mode-S signal obtained by ADS-B. Table 1 lists the seven sound sources targeted in the analysis and the number of data for each noise source. The sound sources of Nos. 1-1 to 1-6 in the table are jet aircraft and that of No. 1-7 is a turboprop, and the total number of data is 4,344. Generally, even for the same aircraft model, the type of installed engine differs among airline companies, and thus the acoustic characteristics of the aircraft noise should be different. This is why we considered the engine type when performing the identification, as in previous studies [9–11]. Although the engine type is based simply on the aircraft model in this case study, in case study 2 herein the engine type differs even for the same aircraft model. Also, models derived from the same aircraft, such as B737-700 and B737-800, are classified as the same sound source; this is because if the same engine is installed, the frequency characteristics of the engine noise are considered to be the same.

2.2. Method

CNNs are often used for image identification, where the analysis is performed by converting the color shades of the image into two-dimensional numerical data. When RGB colors are also considered, they are analyzed with numerical data based on a three-dimensional array. In the present study, the input data used for the analysis were one-third octave band levels sampled at 1 s intervals for each aircraft noise event. The time range is limited to 60 s centered at the time of $L_{A,Smax}$ in each event. The frequency range of the one-third octave band is also limited from 20 Hz to 16 kHz (in 30 bands) to include the dominant frequency components for each aircraft type. As shown

Table 1 Targeted noise sources used for classification in case study 1.

No.	Classification ID	Aircraft model	Engine type	Number of data
1-1	B737_CFM56_LD	B737-700 B737-800	CFM56-7	1,821
1-2	B767_CF6_LD	B767-300	CF6-80	989
1-3	B777_PW4000_LD	B777-200 B777-300	PW4000	771
1-4	B787_TR1000_LD	B787-8 B787-9	Trent 1000	361
1-5	CRJ700_CF34_LD	CRJ700	CF34	298
1-6	A32_CFM56_LD	A320 A321	CFM56-5	52
1-7	ATR42_PW100_LD	ATR42	PW100	52

Fig. 1 Images of time–frequency characteristics of aircraft noises used as input data to CNN in case study 1. In each figure, the horizontal axis indicates time (0 s to 60 s) and the vertical axis indicates the center frequency of the 1/3 octave band (20 Hz to 16 kHz). One data set is shown as an example from each sound source.

later, because the architecture of the CNN used in this study requires two-dimensional numerical input data comprising 224×224 pixels, the data of the frequency characteristics of $60 \text{ s} \times 30$ bands were converted into that format applying linear interpolation. To visualize the input data, their frequency–time characteristics are shown in Fig. 1. One data set is shown as an example from each sound source. The horizontal and vertical axes indicate time and frequency, respectively. It can be seen that each sound source is broadband noise with components in a wide frequency band.

Of the various architectures that have been proposed for CNNs, the residual network (ResNet) [14] that enables learning in deeper layers is applied in this study. A flow chart of the CNN analysis performed in this study and the parameters of each process (e.g., filter sizes and the number

of filters) are shown in Fig. 2. The ResNet layer depth is 50 (ResNet-50). This training process was repeated 300 epochs to improve the performance of the model. Ten-fold cross-validation was used to evaluate the loss of aircraft type identification with test data. In this method, all the input data were divided into either training or test data in a ratio of nine to one. This validation was repeated 10 times while changing the composition of the training and test data.

The total accuracy of the model was estimated by summing the results of each validation. Because the number of data differed greatly among the sound sources, both the overall correct-answer rate (accuracy) and the *F*-measure for each sound source are calculated and the validity was examined. The accuracy was determined by dividing the number of times that the prediction by the

Fig. 2 Structure of CNN used in this study (ResNet-50), where “conv.” means convolution layer.

Table 2 Correspondence of test-data prediction and correct answer in 10-fold cross validation in case study 1.

No.	Classification ID	N	Precision	Recall	F -measure
1-1	B737_CFM56_LD	1,821	99.5%	99.6%	99.5%
1-2	B767_C76_LD	989	99.3%	99.5%	99.4%
1-3	B777_PW4000_LD	771	99.4%	99.4%	99.4%
1-4	B787_TR1000_LD	361	98.9%	98.3%	98.6%
1-5	CRJ700_CF34_LD	298	99.0%	99.0%	99.0%
1-6	A32_CFM56_LD	52	98.1%	98.1%	98.1%
1-7	ATR42_PW100_LD	52	100.0%	98.1%	99.0%
Accuracy = 99.6%					

aircraft identification system and the field measurement agreed by the total number of samples. This value indicates the percentage of data identified correctly among all the input data. The F -measure was calculated using Eq. (1) with the precision and recall given by Eqs. (2) and (3), respectively:

$$F\text{-measure}_i = \frac{2 \times \text{Precision}_i \times \text{Recall}_i}{\text{Precision}_i + \text{Recall}_i} \quad (1)$$

$$\text{Precision}_i = \frac{\text{TP}_i}{\text{TP}_i + \text{FP}_i} \quad (2)$$

$$\text{Recall}_i = \frac{\text{TP}_i}{\text{TP}_i + \text{FN}_i} \quad (3)$$

Here, TP (true positive) is the rate at which the system correctly identified a sound source from data belonging to that sound source, and conversely FN (false negative) is the rate identified incorrectly as not belonging to that sound source. Meanwhile, FP (false positive) is the rate at which the system incorrectly identified data of a sound source as belonging to that sound source. The subscript “ i ” refers to the sound-source number listed in Table 1.

2.3. Results

The accuracy and F -measure obtained by 10-fold cross-validation are listed in Table 2. The accuracy was very

high, reaching 99.6%; this is a high rate compared with the results of previous studies targeted at jet aircraft noise [9–13]. Moreover, in addition to the accuracy, the F -measure for each sound source was also very high, over 98%. This means that all aircraft models are identified correctly. The number of errors in this case study was 18, of which seven were identified incorrectly as No. 1-1.

3. CASE STUDY 2: LANDING AND TAKE-OFF NOISE MEASURED NEAR NARITA INTERNATIONAL AIRPORT

3.1. CNN Input Data

The field measurements were carried out in December 2016 and December 2017, a total of 10 days, at three locations near a flight path of Narita International Airport in Japan. The recording sites were between 1 km and 20 km south of the end of the airport runway. Because the direction of runway operation changed in the measurement period, the aircraft noise data obtained by the measurements are a mixture of takeoff and landing sounds. The measured data are one-third octave band levels sampled at 1 s intervals by a frequency-analyzing sound level meter (Rion; NL-52). The aircraft model and installed engine type of each aircraft noise event were identified using information provided by the airport company. Table 3 lists

Table 3 Targeted noise sources in case study 2.

No.	Classification ID	Aircraft model	Engine type	Number of data
2-1	A32_CFM56_TO	A320	CFM56-5	195
2-2	A32_V25_TO	A320 A321	V2527 V2530 V2533	302
2-3	A32_V25_LD	A321	V2530 V2533	110
2-4	A33_TR772_LD	A332 A333	TRENT772	132
2-5	B737_CFM56_LD	B737-700 B737-800 B737-900	CFM56-7	191
2-6	B737_CFM56_TO	B737-700 B737-800 B737-900	CFM56-7	224
2-7	B747_CFM6_LD	B747-400	CF6-80	146
2-8	B747_PW40_LD	B747-400	PW4056	144
2-9	B747_GENx-2_LD	B747-8	GENx-2	186
2-10	B767_CFM6_LD	B767-300	CF6-80	631
2-11	B767_CFM6_TO	B767-300	CF6-80	437
2-12	B777_GE90_LD	B777-200 B777-200LR/F B777-300ER	GE90-90 GE90-110 GE90-115	788
2-13	B777_PW40_LD	B777-200	PW4077 PW4090	189
2-14	B777_GE90_TO	B777-200 B777-200LR/F B777-300ER	GE90-90 GE90-110 GE90-115	265
2-15	B787_GENx-1_LD	B787-8 B787-9	GENx-1	249
2-16	B787_GENx-1_TO	B787-8 B787-9	GENx-1	245
2-17	B787_TR1000_LD	B787-8 B787-9	TRENT1000	328
2-18	B787_TR1000_TO	B787-8 B787-9	TRENT1000	162

the 18 sound sources targeted in the analysis and the number of data for each noise source. The total number of data is 4,924. The all sound sources in the table are jet aircraft. As in case study 1, the engine type was considered when classifying the sound sources. Furthermore, takeoff and landing were considered as different sound sources.

3.2. Method

The time and frequency ranges of the input data and the sampling time interval were the same as in case study 1. The frequency–time characteristics are shown in Fig. 3. One data set is shown as an example from each sound

source. The CNN architecture was also the same as that in case study 1; that is, ResNet-50 was applied.

3.3. Results

The accuracy and F -measure obtained by 10-fold cross-validation are listed in Table 4. As in case study 1, the accuracy was very high, reaching 98.3%. Compared with case study 1, the F -measure varies slightly but remains very high at 95.5–99.8%. For the sound sources of Nos. 2-7 and 2-8, whose F -measures were relatively small, the total number of errors was 17 cases, of which eight (47%) were misidentified as the other. Similarly, for the sound sources

Fig. 3 Images of time–frequency characteristics of aircraft noises used as input data to CNN in case study 2. In each figure, the horizontal axis indicates time (0 s to 60 s) and the vertical axis indicates the center frequency of the 1/3 octave band (20 Hz to 16 kHz). One data set is shown as an example from each sound source.

of Nos. 2-15 and 2-17, the total number of errors was 29 cases, of which 14 (48%) were misidentified as the other. In case study 2, the data used for the investigation were mixed takeoff and landing sounds, but in very few cases (less than 0.1% of the total) was takeoff sound misidentified as landing sound or vice versa. Also, the identification of takeoff sound was slightly higher than that of landing sound, and the average F -measure for takeoff and landing was 98.7% and 97.6%, respectively.

4. DISCUSSION

4.1. Effectiveness of Identifying Jet Aircraft Models

Herein, the aim is to identify jet aircraft models by using a CNN whose input data are the frequency characteristics of aircraft noise obtained under airport flight paths, with the assumption being that the system would be used to

count the number of flights. The resulting accuracies were very high, and a correct answer rate of 98% was obtained in both case studies. This suggests that this system could be used to count the number of flights for each aircraft model and/or engine type with high accuracy. However, some misidentification occurred, and there is room for examining their influence on day-evening-night level L_{den} . In addition, because the data used for the analysis were obtained only in autumn and winter, it is necessary to consider whether the system can cope with changes in the frequency characteristics due to weather conditions.

4.2. Characteristics of Misidentification

Regarding the misclassifications in case study 1, instances of identifying sound sources other than No. 1-1 as No. 1-1 are conspicuous. Because there are more data

Table 4 Correspondence of test-data prediction and correct answer in 10-fold cross validation in case study 2.

No.	Classification ID	<i>N</i>	Precision	Recall	<i>F</i> -measure
2-1	A32.CFM56.TO	195	97.4%	96.9%	97.2%
2-2	A32.V25.TO	302	99.7%	99.3%	99.5%
2-3	A32.V25.LD	110	99.1%	100.0%	99.5%
2-4	A33.TR772.LD	132	99.2%	95.5%	97.3%
2-5	B737.CFM56.LD	191	98.4%	99.5%	99.0%
2-6	B737.CFM56.TO	224	98.7%	98.7%	98.7%
2-7	B747.CF6.LD	146	95.3%	96.6%	95.9%
2-8	B747.PW40.LD	144	95.8%	95.1%	95.5%
2-9	B747.GEnx-2.LD	186	99.5%	98.9%	99.2%
2-10	B767.CF6.LD	631	98.6%	99.2%	98.9%
2-11	B767.CF6.TO	437	98.9%	98.6%	98.7%
2-12	B777.GE90.LD	788	98.6%	98.6%	98.6%
2-13	B777.PW40.LD	189	99.5%	95.8%	97.6%
2-14	B777.GE90.TO	265	99.6%	100.0%	99.8%
2-15	B787.GEnx-1.LD	249	96.0%	96.4%	96.2%
2-16	B787.GEnx-1.TO	245	98.0%	100.0%	99.0%
2-17	B787.TR1000.LD	328	96.1%	96.6%	96.4%
2-18	B787.TR1000.TO	162	98.1%	97.5%	97.8%
Accuracy = 98.3%					

for sound source No. 1-1 than for any of the other sound sources, sound source No. 1-1 also has the most learning data. There is therefore a possibility of over learning, that is, that robust learning is carried out only for a specific sound source. Consequently, learning with approximately equal numbers of data among all aircraft models and engine types is required. For this purpose, it is necessary to continue collecting sound sources for those models with few data, such as Nos. 1-6 and 1-7.

Regarding the misidentifications in case study 2, these were relatively common between Nos. 2-7 and 2-8 and between Nos. 2-15 and 2-17. The aircraft models of Nos. 2-7 and 2-8 were the same, although the engine type was different. This also applies to the misidentification between the sound sources of Nos. 2-15 and 2-17. Furthermore, all of these four sound sources are landing noises. These results suggest that sound sources other than engine noise contribute to the frequency characteristics of these landing sounds. Because the engine thrust is reduced when approaching the airport, we reason that the engine sound contributes far less to landing noise than to takeoff noise, which may have influenced the identification results. This is also suggested by the identification accuracy of takeoff sound being higher than that of landing sound.

4.3. Toward Identification at a Given Monitoring Site

If it becomes possible to identify aircraft models at a given monitoring site without it having to be under the flight path, then this identification system could also be used to assess the validity of aircraft noise prediction comparing with the field measurement value. The frequency characteristics of aircraft noise are changed greatly by

the excess attenuation due to the ground surface at the side of the flight path. Because it is yet to be determined whether the system that learned the features of aircraft noise in this study could be used for identification at other monitoring sites, expanding the versatility of this system is on the agenda of future work. We aim to improve the effectiveness of this system by adding data obtained at other monitoring sites, such as those beside the flight path and those far from the flight path.

Also, in the monitoring site where aircraft noise level is low, it may be difficult to identify the aircraft model due to the influence of background environmental noise. In particular, other intermittency traffic noises at the site may be misidentified as aircraft noise. In order to prevent such misidentification with other noise sources, it is effective to use the monitoring technique for detecting the direction of sound arrival [15]. In addition, we think that it may be effective to make the other environmental noise to be learned as “other noise source.”

5. CONCLUSION

In this study, we aimed to identify jet aircraft models by applying a CNN whose input data were the one-third octave band levels of aircraft noise obtained under the flight paths around Osaka International Airport and Narita International Airport. The assumption was that this identification system would be used to estimate the number of flights to create noise maps. The identification accuracy was very high in two case studies, with the correct-answer rate reaching 98% in both. This suggests that the present system can count the number of jet aircraft flights for each engine type with very high accuracy. We would like

to develop a more versatile system by making it possible to adapt to differences in the monitoring sites and to distinguish from other noise sources.

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