DESCRIPTION AND DISCUSSION ON DCASE2020 CHALLENGE TASK 2: UNSUPERVISED ANOMALOUS SOUND DETECTION FOR MACHINE CONDITION MONITORING

Yuma Koizumi\textsuperscript{1}, Yohei Kawaguchi\textsuperscript{2}, Keisuke Imoto\textsuperscript{3}, Toshiki Nakamura\textsuperscript{2}, Yuki Nikaido\textsuperscript{2}, Ryo Tanabe\textsuperscript{2}, Harsh Purohit\textsuperscript{2}, Kaori Suefusa\textsuperscript{2}, Takashi Endo\textsuperscript{2}, Masahiro Yasuda\textsuperscript{1}, Noboru Harada\textsuperscript{1},

\textsuperscript{1}NTT Corporation, Japan, koizumi.yuma@ieee.org
\textsuperscript{2}Hitach, Ltd., Japan, yohei.kawaguchi.xk@hitachi.com
\textsuperscript{3}Doushisha University, Japan, keisuke.imoto@ieee.org

ABSTRACT

This paper presents the details of the DCASE 2020 Challenge Task 2: Unsupervised Detection of Anomalous Sounds for Machine Condition Monitoring. The goal of anomalous sound detection (ASD) is to identify whether the sound emitted from a target machine is normal or anomalous. The main challenge of this task is to detect unknown anomalous sounds under the condition that only normal sound samples have been provided as training data. We have designed a DCASE challenge task which contributes as a starting point and a benchmark of ASD research; the dataset, evaluation metrics, a simple baseline system, and other detailed rules. After the challenge submission deadline, challenge results and analysis of the submissions will be added.

Index Terms— Anomaly detection, dataset, acoustic condition monitoring, DCASE Challenge

1. INTRODUCTION

Anomalous sound detection (ASD)\textsuperscript{[1]–[5]} is the task to identify whether the sound emitted from a target machine is normal or anomalous. Automatically detecting mechanical failure is an essential technology in the fourth industrial revolution, including artificial intelligence (AI)–based factory automation. Prompt detection of machine anomaly by observing its sounds may be useful for machine condition monitoring. For connecting Detection and Classification of Acoustic Scenes and Events (DCASE) challenge which includes a sound emitted from the target machine. ADS is an identification problem of determining whether the state of the target machine is a normal or an anomaly from \(x\).

The main challenge of this task is to detect unknown anomalous sounds under the condition that only normal sound samples have been provided as training data\textsuperscript{[1]–[5]}. In real-world factories, actual anomalous sounds rarely occur and are highly diverse. Therefore, exhaustive patterns of anomalous sounds are impossible to deliberately make and/or collect. This means we have to detect unknown anomalous sounds that were not observed in the given training data. This point is one of the major differences in premise between ASD for industrial equipment and the past supervised DCASE challenge tasks and real-world problems, we organize a new DCASE task “unsupervised-ASD”.

The main challenge of this task is to detect unknown anomalous sounds under the condition that only normal sound samples have been provided as training data\textsuperscript{[1]–[5]}. In early studies, acoustic features for detecting anomalies are designed based on the mechanical structure of the target machine\textsuperscript{[18–20]}. Benefiting from the development of deep learning, deep neural network (DNN)–based methods that do not require knowledge of the target machine are also actively being studied\textsuperscript{[21–28]}. However, although recent studies published large scale datasets for ASD\textsuperscript{[29–31]}, many of these studies have been evaluated with different datasets and metrics, and it results in difficult to make a fair comparison of the effectiveness and characteristics of these methods. We believe that creating a benchmark for ASD by designing a unified dataset and metrics would contribute both accelerating research in this area and industrial use of the latest technologies.

We have designed a DCASE challenge task which contributes as a starting point and a benchmark of ASD research. The dataset, evaluation metrics, a simple baseline system, and other detailed rules are designed so that they did not deviate from the real-world issues.

2. UNSUPERVISED ANOMALOUS SOUND DETECTION

Let \(L\)-point-long time-domain observation \(x \in \mathbb{R}^L\) be an observation which includes a sound emitted from the target machine. ADS is an identification problem of determining whether the state of the target machine is a normal or an anomaly from \(x\).

To estimate the state of the target, the anomaly score is calculated. Here, the anomaly score takes a large value when the input signal seems to be anomalous, and vice versa. To calculate the anomaly score, we construct an anomaly score calculator \(A\) with parameter \(\theta\). Then, the target is determined to be anomalous when the anomaly score \(A_\theta(x)\) exceeds the pre-defined threshold value \(\phi\) as

\[
\text{Decision} = \begin{cases} 
\text{Anomaly} & (A_\theta(x) > \phi) \\
\text{Normal} & (\text{otherwise}) 
\end{cases}
\]

(1)

It is obvious from (1), we need to design \(A\) so that \(A_\theta(x)\) takes a large value when the audio-clip \(x\) is an anomaly. Intuitively, it seems to be a design problem of a classifier for a two-class classification problem. However, this task cannot be solved as a simple classification problem, because only normal sound samples have been provided as training data in the unsupervised-ASD scenario. Thus, the main research question of this task is: how can anomalies be detected without anomalous training data?
3. TASK SETUP

3.1. Dataset

The data used for this task comprises parts of ToyADMOS \cite{30} and the MIMII Dataset \cite{21} consisting of the normal/anomalous operating sounds of six types of toy/real machines. These anomalous sounds in these datasets were collected by deliberately damaging target machines. The following six types of toy/real machines are used in this task: Toy-car and Toy-conveyor from ToyADMOS, and Valve, Pump, Fan, and Slide rail from MIMII Dataset. For simplifying the task, we used only the first channel of multi-channel recordings; all recordings are regarded as single-channel recordings of a fixed microphone. Each recording is a single-channel (approximately) 10-sec length audio that includes both a target machine’s operating sound and environmental noise. The sampling rate of all signals has been downsampled to 16 kHz. We mixed a target machine sound with environmental noise, and only noisy recordings are provided as training/test data. The environmental noise samples were recorded in several real factory environments. For the details of the recording procedure, please refer to the papers of ToyADMOS and MIMII Dataset.

In this task, we define two important terms: Machine Type and Machine ID. Machine Type means the kind of machine, which in this task can be one of six: toy-car, toy-conveyor, valve, pump, fan, and slide rail. Machine ID is the identifier of each individual of the same type of machine, which in the training dataset can be of three or four and that of test dataset can be three.

Development dataset includes (i) around 1,000 samples of normal sounds for training and (ii) 100–200 samples each of normal and anomalous sounds for the test for each Machine Type and Machine ID. Evaluation dataset consists of around 400 test samples for each Machine Type and Machine ID, none of which have a condition label (i.e., normal or anomaly). Note that the Machine IDs of the evaluation dataset are different from those of the development dataset. Thus, we also provide the additional training dataset which includes around 1,000 normal samples for each Machine Type and Machine ID used in the evaluation dataset.

3.2. Evaluation metrics

This task is evaluated with the area under the receiver operating characteristic (ROC) curve (AUC) and the partial-AUC (pAUC). The AUC is an AUC calculated from a portion of the ROC curve over the pre-specified range of interest. In our metric, the pAUC is calculated as the AUC over a low false-positive-rate (FPR) range $[0, p]$. The AUC and pAUC are defined as

$$\text{AUC} = 1 - \frac{1}{N_.N_+} \sum_{i=1}^{N_.} \sum_{i=j}^{N_+} \mathcal{H}(A_\theta(x_i^+) - A_\theta(x_i^-)),$$

$$\text{pAUC} = \frac{1}{[pN_.]N_+} \sum_{i=1}^{[pN_.]} \sum_{i=j}^{N_+} \mathcal{H}(A_\theta(x_i^+) - A_\theta(x_i^-)),$$

where $\mathcal{H}(\cdot)$ is the floor function and $\mathcal{H}(a)$ is the hard-threshold function which returns 1 when $a > 0$ and 0 otherwise. Here, $x_i^-$ and $x_i^+$ are normal and anomalous test samples, respectively, and have been sorted so that their anomaly scores are in descending order. Here, $N_.$ and $N_+$ are the number of normal and anomalous test samples, respectively.

The reason for the additional use of the pAUC is based on practical requirements. If an ASD system gives false alerts frequently, we cannot trust it, just as "the boy who cried wolf" could not be trusted. Therefore, it is especially important to increase the true-positive rate under low FPR conditions. In this task, we will use $p = 0.1$.

3.3. Baseline system and results

The baseline system is a simple autoencoder (AE)-based anomaly score calculator which is used in several conventional studies. The anomaly score is calculated as the reconstruction error of the observed sound. To obtain small anomaly scores for normal sounds, the AE is trained to minimize the reconstruction error of the normal training data. This method is based on the assumption that the AE cannot reconstruct sounds that are not used in training, that is, unknown anomalous sounds.

| Machine Type | AUC | pAUC | Machine Type | AUC | pAUC | Machine Type | AUC | pAUC |
|--------------|-----|------|--------------|-----|------|--------------|-----|------|
| (a) Toy-car |     |      | (b) Toy-conveyor |     |      | (c) Fan |     |      |
| 1 (dev.) | 81.36 ± 1.15 | 68.40 ± 0.92 | 1 (dev.) | 78.07 ± 0.79 | 64.25 ± 0.99 | 0 (dev.) | 54.41 ± 0.47 | 49.37 ± 0.10 |
| 2 (dev.) | 85.97 ± 0.58 | 77.72 ± 0.90 | 2 (dev.) | 64.16 ± 0.53 | 56.01 ± 0.71 | 2 (dev.) | 73.40 ± 0.58 | 54.81 ± 0.34 |
| 3 (dev.) | 63.30 ± 1.03 | 55.21 ± 0.37 | 3 (dev.) | 75.35 ± 1.39 | 61.03 ± 1.00 | 4 (dev.) | 61.61 ± 1.08 | 53.26 ± 0.40 |
| 4 (dev.) | 84.45 ± 1.87 | 68.97 ± 2.37 | 5 (eval.) | - | - | 6 (dev.) | 73.92 ± 0.54 | 52.35 ± 0.51 |
| 5 (eval.) | - | - | 6 (eval.) | - | - | 1 (eval.) | - | - |
| 6 (eval.) | - | - | 5 (eval.) | - | - | 3 (eval.) | - | - |
| 7 (eval.) | - | - | 6 (eval.) | - | - | 5 (eval.) | - | - |

Table 1: Baseline system results

- **Development dataset** includes (i) around 1,000 samples of normal sounds for training and (ii) 100–200 samples each of normal and anomalous sounds for the test for each Machine Type and Machine ID.
- **Evaluation dataset** consists of around 400 test samples for each Machine Type and Machine ID, none of which have a condition label (i.e., normal or anomaly).
In the baseline system, we first calculate a log-mel-spectrogram of the input \( X \in \mathbb{R}^{P \times T} \), and \( F \) and \( T \) are the number of mel-filters and time-frames, respectively. Then, the log-mel spectrum at \( t \) is concatenated with before/after \( P \) frames as \( \phi_t = (X_{t-P}, ..., X_{t+P}) \), and used the acoustic feature at \( t \). Then, anomaly score is calculated as

\[
A_{\theta}(x) = \frac{1}{T} \sum_{t=1}^{T} \| \phi_t - D_{\theta_D}(E_{\theta_E}(\phi_t)) \|_2^2, \tag{4}
\]

where \( \| \cdot \|_2 \) is \( \ell_2 \) norm, and \( E \) and \( D \) are the encoder and decoder of the AE whose parameters are \( \theta_E \) and \( \theta_D \), respectively. Thus, \( \theta = \{ \theta_E, \theta_D \} \).

The hyper-parameters of the baseline system are as follows. The encoder/decoder of AEs consists of one input fully-connected-neural-network (FCN) layer, 3 hidden FCN layers, and one output FCN layer. Each hidden layer has 128 hidden units, and the dimension of the encoder output is 8. The rectified linear unit (ReLU) is used after each FCN layer except the output layer of the decoder. We stopped the training process after 100 epochs, and the batch size was 512. Te ADAM optimizer was used, and we fix the learning rate as 0.001.

Results of the baseline system are presented in Table [1]. The AUC and pAUC on the development dataset was evaluated using several types of GPUs (RTX 2080, etc.). Because the results produced with a GPU are generally non-deterministic, the average standard deviation from these 10 independent trials (training and testing) are shown in the table.

4. CHALLENGE RESULTS

Challenge results and analysis of the submitted systems will be added for the official submission of the paper to the DCASE 2020 Workshop.

5. CONCLUSIONS

This paper presented an overview of the task and analysis of the solutions submitted to DCASE 2020 Challenge Task 2. Challenge results and analysis of the submitted systems will be added for the official submission of the paper to the DCASE 2020 Workshop.

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