HAASD: A dataset of Household Appliances Abnormal Sound Detection

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ABSTRACT

Intelligent household appliance sound event detection and classification is an evolving research field for intelligent diagnosis and evaluation of household appliances. In this paper, we identified three major barriers to research in this area—the lack of a common taxonomy, the scarcity of negative samples, and the low signal-to-noise ratio of household appliances' sound signals. In order to solve these problems, we proposed appliance fault or abnormal sound detection and a new dataset household appliances abnormal sound detection (HAASD), which is divided into two categories: normal sound and abnormal sound. Each category has more than one background noise file. Noise data annotated in the mode. A series of experiments using the baseline classification system were used to study the challenges of the data set, and multiple evaluation indicators of different characteristics in different classifiers were compared.

CCS Concepts

• Computing methodologies → Artificial intelligence • Applied computing→Sound and music computing

Keywords

Household appliances sound; classification; dataset; intelligent fault diagnosis; machine learning

1. INTRODUCTION

Since the development of sensor technology and computer science, it has become more and more convenient to acquire and store data.

Fault diagnosis methods based on models such as Gaussian model, hidden Markov model, and negative matrix decomposition show their weaknesses in processing large amounts of data [1], [2]. At the same time, in recent years, a lot of research and discussion on intelligent fault diagnosis methods have been carried out in an effort to face the challenges of the big data era [3] - [4]. The deep learning technology shows particularly good performance in both image classification tasks and audio classification tasks [5].

At the same time, the auditory recognition task is mainly focused on voice, music and environmental sound tasks [6] - [10]. The analysis of abnormal sounds of machinery and equipment in industrial manufacturing is lagging behind in the research of smart speakers and hearing aids. Although there are some studies related to motors, bearings, and gears, for example [11] using deep neural networks to turn faults through the motor for fault diagnosis. But without an open data set, one of the objective obstacles to more active research in this area is the strong division and the difficulty of achieving comparability and repeatability. We surveyed the mechanically relevant small and medium dataset and found that this open dataset[1] is not only extremely scarce but also extremely difficult to access. This is in stark contrast to computer vision. Image datasets such as MNIST[2] and CIFAR[3] can easily be studied in various aspects. Therefore, we hope to deposit an open study of fault diagnosis of smart products in the following ways:

- Provide normal and abnormal operating noise of publicly available household appliances and various background noise data sets
- An assessment of the classification of humans and experienced workers for this dataset
- Provide a baseline machine learning classifier for this dataset and compare and evaluate and correlate the baseline system

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[1] Most datasets are listed on a website maintained by Toni Heittola: http://www.cs.tut.fi/˜heittolt/datasets.html [Accessed Aug. 5, 2015]

[2] http://yann.lecun.com/exdb/mnist/ [Accessed Aug. 5, 2015]

[3] http://www.cs.toronto.edu/˜kriz/cifar.html [Accessed Aug. 5, 2015]

- Provide and evaluate the convolutional neural network classifier for this dataset
- Provide methods and related codes for the feature analysis of this dataset
- Provide methods and related codes for adding various types of noise in the dataset

2. THE HAASD DATASET

In the production environment, using B&K microphone, the Pluse data acquisition front end to collect mechanical noise from different normal and abnormal washing machines on the production line, using the sampling frequency of 64kHZ to collect the mechanical noise generated by the washing machine in different modes, the collected data There are all kinds of complicated information. These machines are sorted and tagged by experienced professionals and finally processed into normal and anomalous categories and processed into data sets. Here we have the following definitions for the abnormal sound of the washing machine: 1. There are irregular sounds during operation; 2. There is a sharp sound during operation; 3. There are interference sounds during operation [12], [13]. The dataset is suitable for unsupervised and supervised learning. This project[4] has been supported by the National Natural Science Foundation so that the data set can be smoothly carried out from collection to labeling to finishing. Both the dataset and the baseline are public on Github.

2.1 Dataset Structure

The HAASD dataset is divided into two categories: normal sound and abnormal sound. According to different types of household appliances, there are noise data with multiple modes in addition to the background noise file. (All background noises here are normal sounds by default).

The abnormal sound data of different household appliances are sorted into different folders. For example, as shown in Table 1,in the washing machine running noise data set, 130 sub-files are included in the abnormal data folder, and the abnormal sound of the dehydration motor is closed, and the dehydration fault is closed abnormal sound, eccentric block closing abnormal dehydration sound, open cover washing abnormal sound, washing motor abnormal sound and background noise; normal data contains 100 sub-files, collecting cover dehydration noise, washing noise, far-distance near-distance dehydration noise. The dataset size is 366M. According to the continuous advancement of household appliance noise detection research, the datasets of household appliances' abnormal sounds are also expanding, and the categories are also increasing. The household appliance noise dataset will update the dataset and explain it at different stages based on experimental research.

Table 1. Household appliance data category

Washing machine	**Drum washing machine**	**Refrigerator**	**Air conditioning**
Close the abnormal sound of the dehydration motor	Dehydration motor abnormal sound	The minimum opening door compressor abnormal sound	Cooling abnormal sound
Close the dehydration fault machine running sound	Dehydration fault machine running sound	The lowest level closed door compressor abnormal sound	Dehumidification abnormal sound
Add eccentric block to cover abnormal dehydration sound	Add eccentric block dehydration abnormal sound	The most high-grade door opening compressor abnormal sound	Heating abnormal sound
Washing open cover abnormal sound	Abnormal washing sound	The most high-grade closing compressor abnormal sound	Windshield swing abnormal sound
Washing motor abnormal sound	Washing motor abnormal sound	Lowest level compressor normal sound	Cooling normal sound
Dehydration/washing normal sound	Dehydration/washing normal sound	The highest level compressor normal sound	Heating normal sound

[4] https://github.com/JYongSmile/paper-2018-HAASD

2.2 Input Setup

A random selection from the original training raw waveform data can be input into the baseline model. The selected parts are different in each period. When making the data set, all the original data uses a random function, so that the training of the data is completely random and there is no emphasis.

In order to improve the data reading speed of the model, the data set production format adopts binary data storage mode. The sampling window size for each data is variable. Then, the data sets are respectively made according to different sampling rates and different sampling windows of different features. (Researchers using the dataset can resample the data at different sample rates for different dimensions.) The binary datasets are created together along with the production methods and code[5].

3. ABNORMAL SOUND DETECTION

3.1 Human Detection

In the field of fault diagnosis, it is one of the frequently used methods to judge the abnormal position and severity of the machine based on the mechanical running noise. However, due to the extremely complex, dynamic and unknown background noise in industrial manufacturing production environments, and the target mechanical noise signals collected in complex environments contain noise from a variety of other devices, the real need may be a small part. From the point of view of sound detection, information containing useful features is often buried in mechanical noise data with low signal-to-noise ratio and difficult to extract. It is difficult to judge from audio data without experience. We have also proved this through verified

[5] The binary dataset can quickly read the data in the case where the data volume is getting larger and larger, and the provided data set making code is a matlab script.

experiments. The accuracy rate of non-experienced people is between 50% and 60%, and the accuracy of experienced workers is between 80% and 90%. This undoubtedly takes up a lot of human resources in industrial production.

3.2 Baseline Machine Detection

Experienced workers have the ability to detect abnormal sound of household appliances, then we will establish some baseline methods to detect the abnormal sound of household appliances. The purpose of the baseline system is not to build a stable detection system [11], but to investigate whether it is possible to analyze the data through machine learning and extract data features for machine detection systems. The abnormal sound of the household appliance contains complicated information and low signal-to-noise ratio. So far, there is no matching feature to quickly detect the abnormal sound. Therefore, we do not subject any appliance pre-processing to the noise data of the appliance, and directly sample the time domain data as the input of the baseline model. Here we provide four baseline classifiers: random forest ensemble, gradient boost decision tree model (GBDT) The support vector machine model (SVM) with RBF as the kernel function and the k-nearest neighbors (k-NN). Use these models to learn household appliance noise datasets through a three-fold cross-validation system[6].

3.3 Baseline Machine Detection Result

The household appliance noise dataset ranges from 68.1% of the SVM classifier to 84.92% of the random forest. The gradient boost decision tree classifier is followed by 82.2%. In the middle is the K-NN classifier is 73.78%. Referring to Figure 1, it is possible to show significant dispersion results between these classifiers. The SVM classifier showed very poor results. Random forest classification performance is good, and experienced workers reach the same level of detection. The three forests, the random forest ensemble, the gradient decision tree and the k-NN, are highly accurate in terms of accuracy. The average accuracy rate is over 98%.

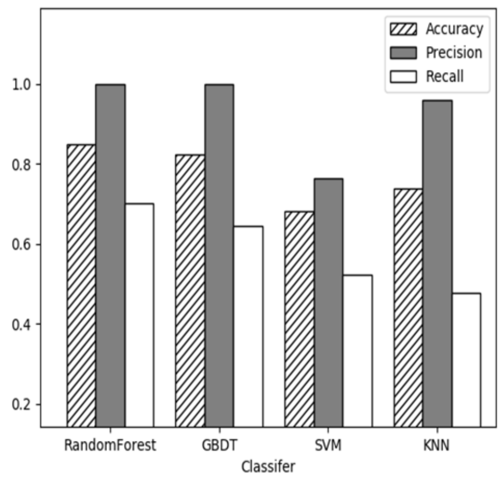

Figure 1. Comparison of accuracy, precision and recall rate between different classifiers.

6 The cross-validation mechanism used in the experiment, the parameters here can be tuned according to the results

It is still difficult to evaluate the pros and cons of the detection classifier in the field of fault diagnosis with the only accuracy. Especially in the case of unbalanced positive and negative samples, the accuracy index has great defects [14], [15]. As shown in Figure 2, we can see that the random forest and gradient boost decision tree classifiers are better through the random forest ensemble, gradient boost decision tree, support vector machine and k-NN ROC curve. The random forest classifier AUC is 0.7659, and the gradient elevation decision tree classifier AUC is 0.705.

In general, these baseline methods perform poorly compared to experienced workers' corresponding noise detection systems, but some of the sound characteristics are more pronounced to achieve good performance. For example, the recordings in many sound/background noise categories are very vague for human listeners who are having difficulty obtaining fairly high scores in automated systems. Compared with the k-NN classification method, the SVM classifier performs better for the frequency domain input of household appliance noise data. It should be noted here that the proposed baseline classification method is relatively simple and has not been pre-processed with too many features [10], [16]. The author's research will continue to evaluate convolutional neural networks and recurrent neural networks.

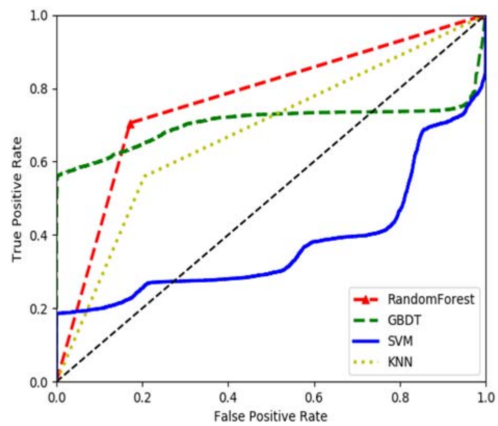

Figure 2. ROC curve of Random forest, GBDT, SVM, k-NN baseline classifier.

3.4 Convolutional Neural Network Detection

Convolutional neural networks show good performance on both image and audio classification tasks. We also used convolutional neural networks to make initial attempts at the HAASD data set. We built a three-layer convolutional neural network, and the neural network architecture is shown in Figure 3. It consists of three convolutional layers, three pooling layers, one fully connected layer, and finally outputs the prediction results using the softmax layer. Among them, ReLU is applied to each convolution layer. During training, from the input of the data to the data processing, to the feature extraction of the three-layer convolutional layer, finally, the final loss value is obtained by the cross-entropy function. The smaller the Losses value and the convergence, the more convergent and accurate the neural network model is. After 20,000 iterations of training data, the trained model parameters are saved and tested, and the prediction accuracy reaches 85.49%. After evaluation, the generalization ability of convolutional neural networks is stronger, and it is able to adaptively learn data features. The prediction accuracy of different test sets is better than the baseline method.

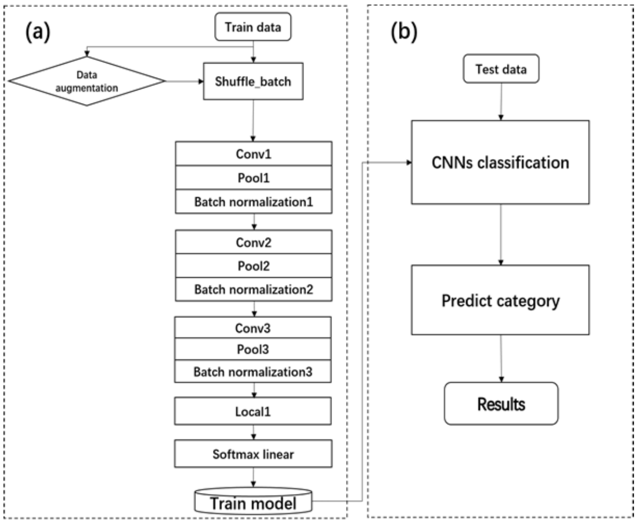

Figure 3. The framework of abnormal sound detection. (a) The training phase and (b) the test phase.

4. CONCLUSIONS

This paper is mainly to provide the first public household appliance noise data set in the field of household appliance intelligent diagnosis. It can detect the abnormal sound of household appliances through various machine learning algorithms and classifiers. This enriches the research in the field of intelligent diagnosis and promotes the development of the intelligent diagnosis of household appliances. There are still many studies that can be extended on this dataset:

- Investigate past research papers and compare the pros and cons of various algorithms.
- Study the feature extraction methods applicable to various types of household appliance fault sounds for noise and fault detection.
- Evaluate the performance of various deep neural networks in the field of deep learning on household appliance noise detection
- Unsupervised learning of household appliance noise data sets
- Research on online appliance intelligent diagnosis system

Of course, this data set also has many shortcomings. First, the industrial environment is complex, and the background noise provided is single. Second, the household audio data set is only intended to perform abnormal sound detection and cannot identify the type and severity of the fault. This is also one of the challenges that have been studied in the field of fault diagnosis. The abnormal data set of household appliances is only a small part of the field of intelligent diagnosis. It is hoped that more and more data sets of manufacturing industry will be released in the future to jointly promote the development of intelligent diagnosis.

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