Evaluation of 2D Acoustic Signal Representations for Acoustic-Based Machine Condition Monitoring

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Abstract

Acoustic-based machine condition monitoring (MCM) provides an improved alternative to conventional MCM approaches, including vibration analysis and lubrication monitoring, among others. Several challenges arise in anomalous machine operating sound classification, as it requires effective 2D acoustic signal representation. This paper explores this question. A baseline convolutional neural network (CNN) is implemented and trained with rolling element bearing acoustic fault data. Three representations are considered, such as log-spectrogram, short-time Fourier transform and log-Mel spectrogram. The results establish log-Mel spectrogram and log-spectrogram, as promising candidates for further exploration.

Keywords: Machine Condition Monitoring, Detection and Classification of Anomalous Machine Operating Sound, Industrial Sound Analysis, Machine Hearing.

Introduction

Machines are the backbone of industry; their fault-free operation is vital to lower operating cost. To ensure this, condition monitoring approaches such as vibration analysis and lubrication monitoring, among others have been adopted. In industrial settings, it is not uncommon for experienced maintenance engineers to develop an ear-based perception of the health of machines. Acoustic-based machine condition monitoring (MCM) is a means to formalise this observed inert behaviour in experienced maintenance engineers. The analysis of sound for speech, music and acoustic event recognition are well developed for creating smart and interactive technologies [1]. However, in the context of machine fault diagnostics, this presents an emerging research area for the detection and classification of anomalous machine operating sounds (DCAMS). Within the context of DCAMS and the application of deep learning to address anomalous sound detection and classification task, the format of 2D representation of acoustic signal is vital [2]. For speech and music acoustic event recognition, this representation has been addressed [1,3]. Within the domain of machine condition monitoring, this is still required. Therefore, this study mainly investigates the effectiveness of various 2D acoustic signal representation for training a baseline convolution neural network (CNN) to address the task of classification of anomalous machine sound.

Experimental

Experimentation is performed on a rolling-element bearing fault rig with setup consisting of 0.55 kW electric motor driving a lightly-spring-loaded (axial and radial) deep groove ball bearing (SKF 6207) through a drive shaft with a flexible coupling, as shown in Fig. 1.

(a) (b) (c) (d)

Figure 1. Experimental setup: (a) rolling-element bearing fault test rig, (b) test bearing housing, (c) healthy bearing, and (d) bearing with cage defect fault.

The test bearings in Fig. 1 consist of healthy ball bearing and ball bearing with cage defect. Test conditions include running at incremental speeds of 300, 600, 900, 1500 and 2400 rpm. Acoustic data for machine operating sound is acquired, using Ultramic USB ultrasound microphone sampling at 250 kHz and SeaWave software.

Results and discussion

CNN is adopted for the benchmarking task for the 2D acoustic signal representation, as it provides model classification accuracy above 98% [4]. CNN takes its inspiration from the operation of the mammalian visual cortex using a multi-staged process, as shown in Fig. 2. This includes feature extraction stage (convolution, pooling, normalisation, and activation layers) and classification stage (fully connected layer of multilayer perceptron). The convolution layer functions to extract feature set into a feature map, pooling layer reduces the dimensionality of the feature map, and the classification stage performs the classification task using the multilayer perceptron. Table 1 presents the parameters of the adopted baseline CNN architecture. Using the CNN model as a baseline, the effectiveness of the following 2D acoustic signal representations is evaluated: log-spectrogram, short-term Fourier transform (STFT) and log-Mel spectrogram. Benchmarking results are presented in Table 2.

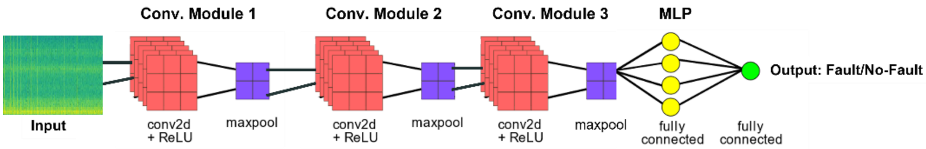

Figure 2. CNN architecture.

Table 1. CNN architecture parameters.

Input	Conv. Module 1	Conv. Module 2	Conv. Module 3	MLP (Multi-Layer Perceptron)
shape= 150x150 sound per class: ~45 (train ~35, val. 10)	shape= 16x16, activation = ReLU, max pooling = 2x2	shape= 32x32, activation = ReLU, max pooling = 2x2	shape= 64x64, activation = ReLU, max pooling = 2x2	Flatten, 512 hidden nodes/ ReLU 1 node/ Sigmoid

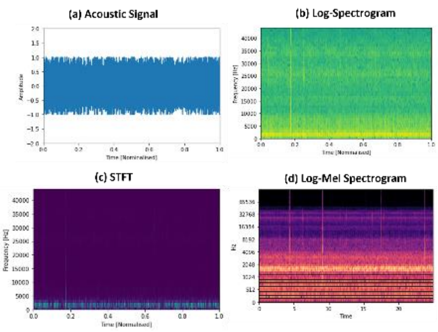

Figure 3. 2D acoustic signal representations.

Table 2. Method benchmarking.

Method + CNN (Not Optimised)	Accuracy (training)
Log-Spectrogram	0.5397
STFT	0.4603
Log-Mel Spectrogram	0.5873

Conclusion

The results establish Log-Mel Spectrogram and Log Spectrogram as promising candidates for further exploration. But, the performance of the CNN model has not been optimised, due to a very limited machine acoustic dataset. Therefore, continuous, or future study seeks to achieve the optimisation of the performance of the CNN model.

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