Building model of processing and identifying engine vibration signal

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Presentation contents

1. Introduction
2. The data sets
3. Fault Classification based on Spectrogram of Vibration Signals and Deep Neutral Networks
4. Conclusion

Introduction

- Bearings are one of the most important parts in motors.
- Bearing's and motor's vibrations patterns depend on operation modes, changes in electrical circuits, and/or mechanical installations and conditions.

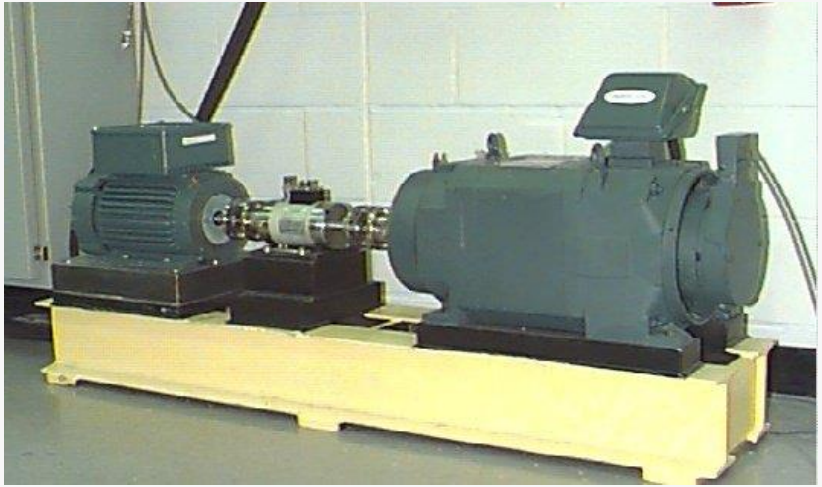
  ⇨ Vibration patterns can be used for state classification, but lots of unwanted noises.
- Vibration patterns can be monitored and detected using different measurement solutions.

  ⇨ Propose to use the Convolution Neural Network to process the data to detect the states of the machines.

The data sets

Case Western Reserve University Bearing Data Center

- 2-HP reliance electric motor, a torque transducer/encoder, a dynamo-meter, and a measurement device using accelerometer.



https://engineering.case.edu/bearingdatacenter

The data sets

Fault types: Ball (rolling - B), outer raceway (OR), inner raceway (IR).

Li, S., Liu, G., Tang, X., Lu, J., & Hu, J. (2017). An Ensemble Deep Convolutional Neural Network Model with Improved D-S Evidence Fusion for Bearing Fault Diagnosis. Sensors, 17(8), 1729.

The data sets

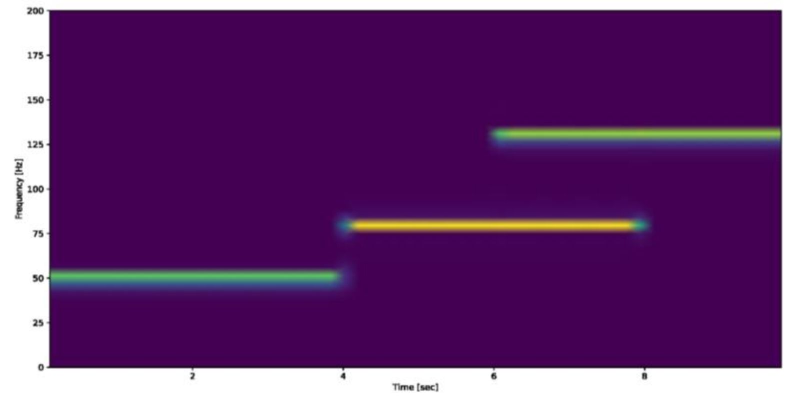
- Data was sampled at 12 kHz, ~10s each record.
- A total of 49 records for 4 types: normal and 3 listed faults.
- Each record was split into 12 segments to form the samples, making 5853 data samples in total.
- 4100 samples (~70%) of the samples were randomly selected for training process.
- 1753 samples (~30%) of the rest are used for testing purpose.

Fault Classification based on Spectrogram of Vibration Signals and Deep Neutral Networks

A. The Spectrogram of a time series signal

- Short-Time Fourier Transform (STFT) creates the time-frequency characteristics of a time series
- Spectrogram as an ”image-like” can be recognized by image recognition tools.

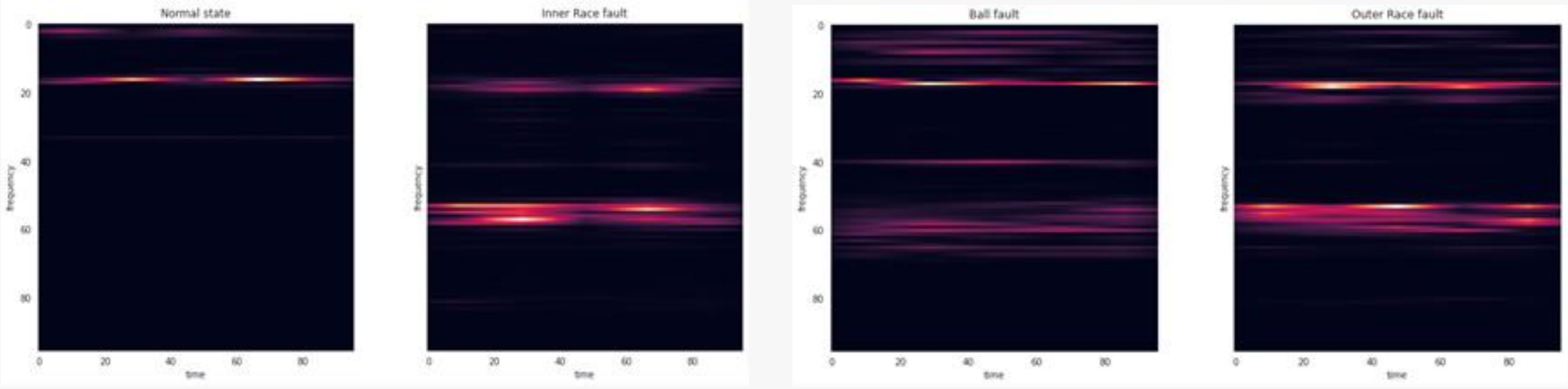
Example: 10s of a time series being a super-position of 3 components: 50Hz in [0s, 4s], 80Hz in [4s, 8s] and 130Hz in [6s, 10s]:



Fault Classification based on Spectrogram of Vibration Signals and Deep Neutral Networks

A. The Spectrogram of a time series signal

Example of STFT of different types of vibration signals (*using Tukey window with r=0.25, data sampling frequency 12 kHz*)



Normal state *Inner race fault* *Ball Fault* *Outer race fault*

Fault Classification based on Spectrogram of Vibration Signals and Deep Neutral Networks

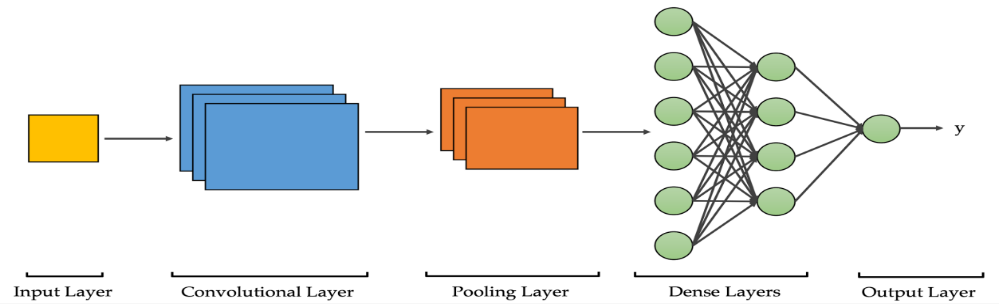
B. Convolutional Neural Network (CNN)

- Very popular deep learning methods.
- Successfully used in many image recognition solutions.
- The CNN structure consists of three main types of layers:

  - Convolution layer.

  - Pooling layer.

  - Fully Connected layer.



Sit, M. et al. (2020). A comprehensive review of deep learning applications in hydrology and water resources. Water Science Technology, vol. 82(12): 2635–2670.

Fault Classification based on Spectrogram of Vibration Signals and Deep Neutral Networks

B. Convolutional Neural Network (CNN)

The proposed CNN architecture:

Input[96 × 96] → Conv[32 × 3 x 3] → Conv[32 × 3 × 3]

→ MaxPool[32 x 2 × 2] → Conv[64 × 3 × 3]

→ Conv[64 × 3 × 3] → MaxPool[64 x 2 × 2]

→ Conv[128 × 3 × 3] → Conv[128 × 3 × 3]

→ MaxPool[128 x 2 × 2] → FC[100 x 1]

→ FC[100 x 1]

Fault Classification based on Spectrogram of Vibration Signals and Deep Neutral Networks

C. Testing Results of the proposed CNN

	N	B 0.007 inch	B 0.014 inch	B 0.021 inch	IR 0.007 inch	IR 0.014 inch	IR 0.021 inch	OR 0.007 inch	OR 0.014 inch	OR 0.021 inch
N	1013	260	0	0	0	0	0	0	0	0
B 0.007 inch	62	153	40	3	0	0	6	41	58	0
B 0.014 inch	0	4	310	19	0	5	5	0	14	8
B 0.021 inch	4	4	10	232	2	0	66	19	25	1
IR 0.007 inch	5	5	2	4	184	0	1	93	70	0
IR 0.014 inch	0	0	138	0	0	212	0	0	0	13
IR 0.021 inch	0	3	8	35	8	0	146	53	109	1
OR 0.007 inch	0	107	2	74	28	0	21	465	269	126
OR 0.014 inch	0	1	7	3	1	0	0	19	423	0
OR 0.021 inch	0	0	140	33	10	33	20	60	0	66

Overall accuracy: 85.8%

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D. Conclusions

- The proposed architecture exhibits an expected good quality result at 85.8% of accuracy.
- The model can be extended to train with different features extracted from the vibration signals and modified loss functions to achieve better accuracy.
- This model can be combined with other classification models to improve the reliability.

Fault Classification based on Spectrogram of Vibration Signals and Deep Neutral Networks

D. Conclusions

Future developments:

- Hardware implementation of a measurement device with integrated classification models (in testing mode).
- Research on solution for simultaneous vibration signals classification (for machines in a production line)
- Research on predictive maintenance solution based on vibration signals.

References

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Thank you
for your attention!