Mixed signal processing and machine learning methods for bearings fault detection: Application in predictive meantenance (Project outline)

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Contents

1 Introduction

Predictive maintenance can be defined as a maintenance philosophy with a set of methods used to predict and prevent machine failure in order to avoid unexpected downtime. This maintenance philosophy when correctly implemented, increases machine life time, and reduces maintenance cost [referecne].

In rotating machines, more than 40 % of machine malfunction can be attributed to bearing defect [references].

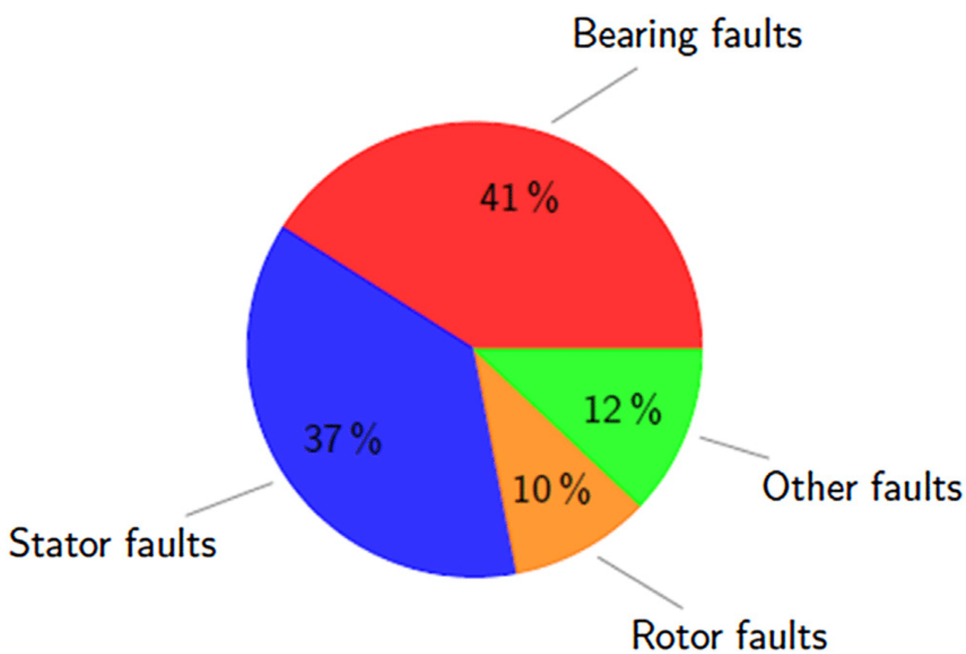

Figure 1: Defect statistic, taken from [reference]

In this project we present a mixed methodology to detect and predict bearing defects. The methodology consists of using signal processing for feature generation and data labelling, and machine learning for defects classification and failure prediction. For a given input dataset, the dataset is decomposed into it subcomponents or basis components. The basis components also called features are then used as input of a supervised learning algorithm for defect classification and failure prediction.

The signal processing methods used are Fourier transform, wavelet transform and Hilbert Huang transform. We focus on ensemble learning and feed forward neural network for classification. Furthermore we show that the back-propagation process in the feed forward neural network can be modelled by an ordinary differential equation, whose solution represents the path of the hidden and output layer weights.

The outline of the project is as followed: In section (chapter) one we give an overview of the signal processing methods. In section (chapter) two we present the machine learning methodology and show that the back-propagation in the feedforward neural network can be modelled as a differential equation. In section (chapter) 3 we present a case study where we apply the methodology defined in section one and two. In section four we present the conclusion of this work.

2 Preview work

3 Signal processing methods

3.1 Overview

We present three signal processing methods for data decomposition or feature generation. The three methods can be described as follow: Given a dataset approximated by a map

$$f : \mathbb{R} \to \mathbb{R} \tag{1}$$

find a space V spanned by a basis $\{\varphi_j\}_{j=0}^{n}$ such that

$$f(x) = \sum_{j=0}^{j=n} \alpha_j \varphi_j. \tag{2}$$

In the context of this work, the basis functions $\{\varphi_j\}_{j=0}^{n}$ are the features derived from the original dataset.

3.2 Fourier transform

3.2.1 Theory

3.2.2 Application

3.3 Wavelet transform

3.3.1 Theory

3.3.2 Application

3.4 Hilbert Huang transform

3.4.1 Theory

The Hilbert-Huang transform is a data decomposition methods that consists of decomposing data in an adaptive fashion. Adaptivity means that rather than imposing an a priory basis such as trigonometric functions, a posteriori basis functions are derived from the data itself [1]. In doing so, the method deals better with nonlinearity and non stationarity which are inherently present in real world data.

This method gives an alternative approach of time-frequency-energy paradigm by using Hilbert spectral analysis and the so call empirical mode decomposition (EMD) to express the nonlinearity and the non stationary in data with instantaneous frequency and instantaneous amplitude [1].

The empirical mode decomposition (EMD) originated from the quest of functions that can be expressed by a time-frequency-amplitude expression, such that the frequency is physically meaningful. Consider a time series $x(t)$. Its Hilbert transform H(t) is given by

$$H(t) = \frac{1}{\pi} P \int_{\infty}^{\infty} \frac{x(\tau)}{t - \tau} \mathrm{d}\tau, \tag{3}$$

where P is the Cauchy principal value. The corresponding time-frequency-amplitude function of $x(t)$ is the analytical function

$$z(t) = x(t) + iy(t) = a(t)e^{i\theta(t)}, \tag{4}$$

where the instantaneous amplitude $a(t)$ and phase $\theta(t)$ can be computed by

$$a(t) = \sqrt{x(t)^2 + y(t)^2} \tag{5}$$

$$\theta(t) = \tan^{-1}\left(\frac{y(t)}{x(t)}\right). \tag{6}$$

Furthermore, the instantaneous frequency $w(t)$ can be derived from the phase $\theta(t)$ as

$$w(t) = \frac{d\theta}{dt}. \tag{7}$$

By setting

$$f(t) = \frac{y(t)}{x(t)},$$

the expression of the instantaneous amplitude $w(t)$ in (7) can be expanded as

$$w(t) = \frac{f'(t)}{1 + f(t)^2} = \frac{y'(t)x(t) - y(t)x'(t)}{x(t)(x(t) + y(t)^2)}. \tag{8}$$

The instantaneous frequency $w(t)$ using the Hilbert transform is not always physically meaning. For example for an arbitrarily function, the instantaneous physical frequency values should be positive. However this is not always the case.

For example if

$$f(x) = \cos(ct) + d \tag{9}$$

where c and d are constants, the instantaneous frequency is given by

$$w(t) = \frac{-c\sin(ct)}{1 + (\cos(ct) + d)^2} \tag{10}$$

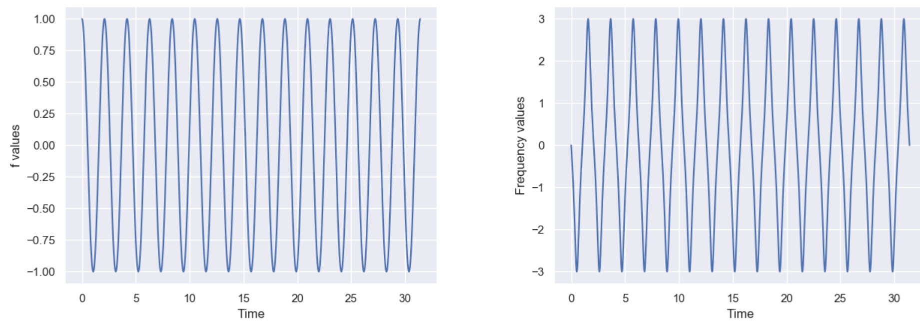

Figure 2: function f and its corresponding frequency

From Figure 2, we see that the instantaneous frequency takes negative values, which is not physically meaning full.

To circumvent this, the Hilbert-Huang transform offers a methodology to obtain from an arbitrarily function or time series $x(t)$ a set of finite subcomponents whose instantaneous frequency are physically meaningful. This methodology let to the empirical mode decomposition.

The necessary condition for obtaining a physical frequency is that $x(t)$ satisfies the approximate local envelope symmetry condition [2].
This condition is expressed in the empirical mode decomposition (EMD) such that an arbitrarily time series $x(t)$ can be decomposed by a sifting process into intrinsic mode function c_i

$$x(t) = \sum_{i=1}^{n} c_i + r_n \tag{11}$$

where the c_i satisfies the approximate local envelope symmetry condition

$$SD_k = \frac{\sum_{t=0}^{T}}{\sum_{t=0}^{T}} < \epsilon \tag{12}$$

where ϵ is a small predefined real number.

3.4.2 Application for bearings fault detection

we consider a vibration signal with sample frequency of 20000Hz rotating speed of 2000 RPM

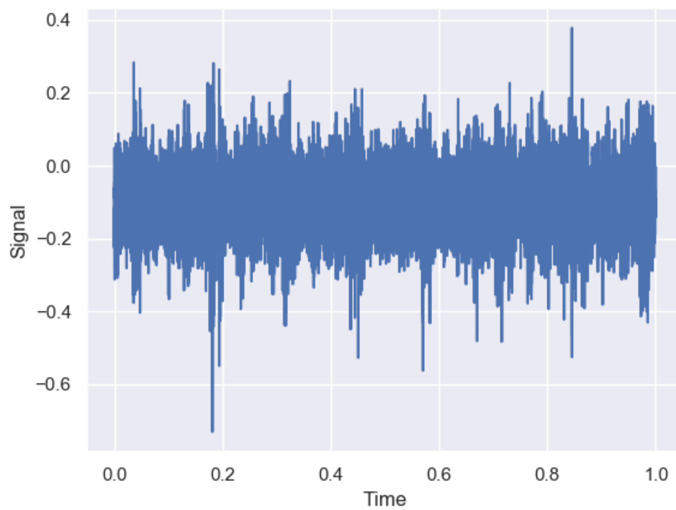

Figure 3: Vibration signal of 1 second snapshot

After applying the empirical mode decomposition on the vibration data from figure 3 we get sixteen intrinsic mode functions

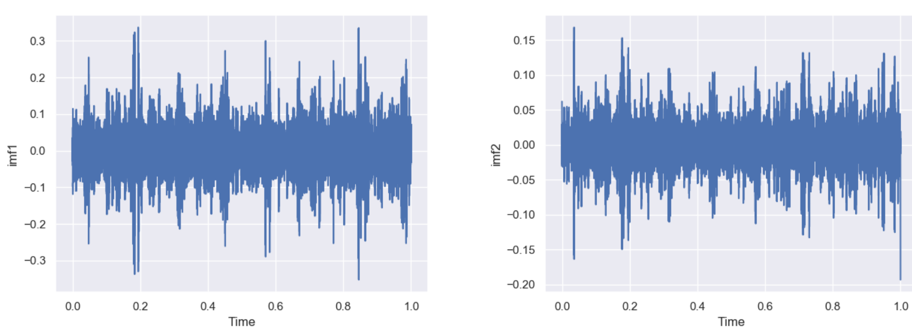

Figure 4: 1th and 2nd intrinsic mode function (imf)

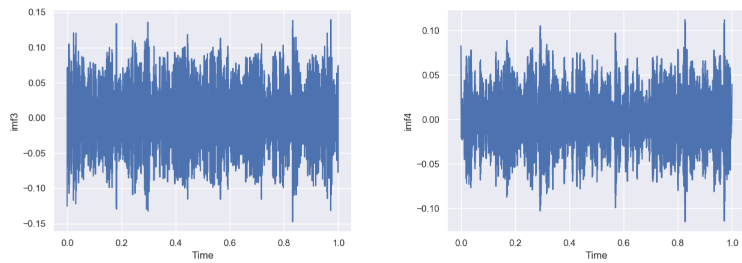

Figure 5: 3rd and 4th intrinsic mode function (imf)

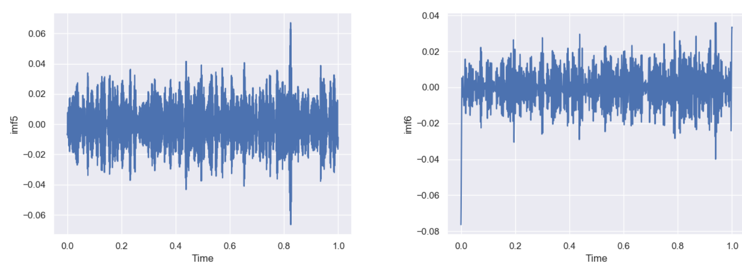

Figure 6: 5th and 6th intrinsic mode function (imf)

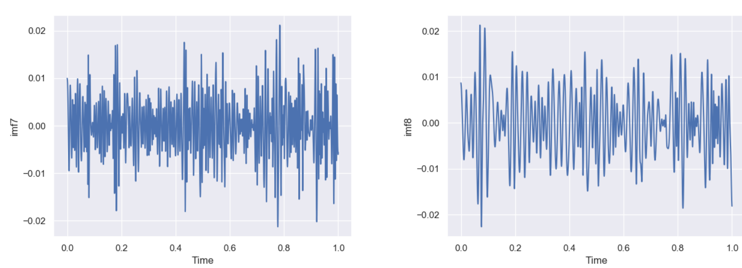

Figure 7: 7th and 8th intrinsic mode function (imf)

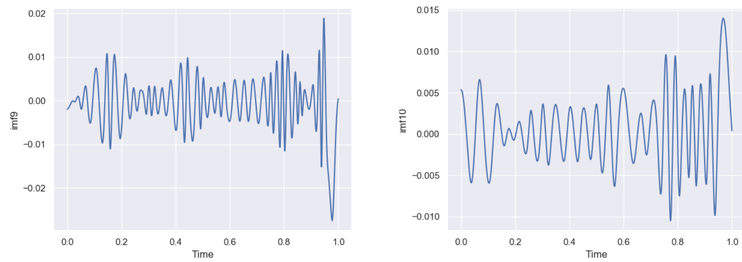

Figure 8: 9th and 10th intrinsic mode function (imf)

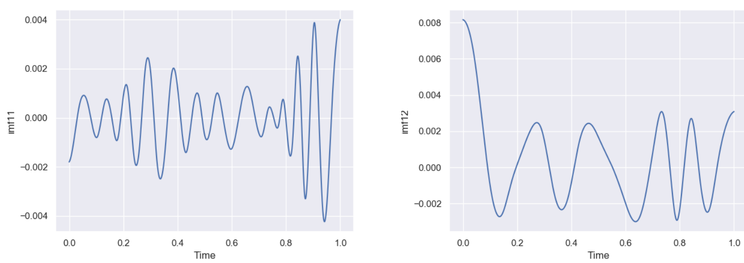

Figure 9: 11th and 12th intrinsic mode function (imf)

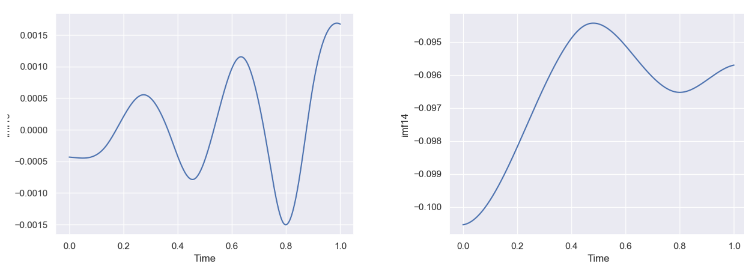

Figure 10: 13th and 14th intrinsic mode function (imf)

4 Machine learning methods

4.1 Overview

5 Result

5.1 Overview

We apply the methodology described in this work to an application for bearing fault detection.

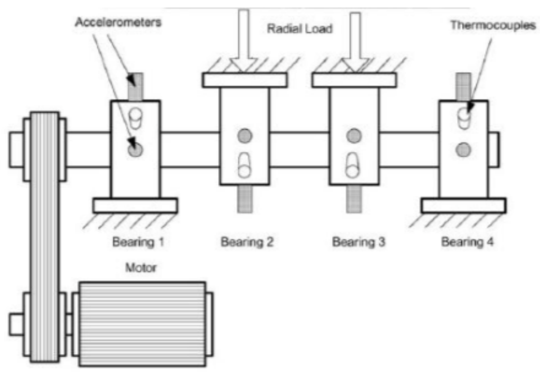

Figure 11: Experimental set up

The data used in this use case was generated by the Intelligence Maintenance system (IMS) [link to the IMS]. Three separate experiments involving four bearings were performed on a motor. In each experiment, a 1-second vibration signal snapshots was recorded every 10 minutes, for a specified time. Each vibrational signal sample consists of 20 480 data points with sampling rate of 20 000 Hz. In this post I will be using the first and the second experiment data [available here (give a link to the data)].

6 Conclusion

References

[1] Norden E. Huang and Zhaohua Wu *A review on Hilbert-Huang Transform: Methods and its Application to Geophysical Studies.* Review of Geophysics, 2008

[2] Norden E. Huang, Zheng Shen, Steven R. Long, Manlic C. Wu, Hsing H.Shih, Quanan Zheng, Nai-Chyuan Yen, Chi Chao Tung and Henry H. Liu *The Empirical mode decomposition and the Hilbert Spectrum for nonlinear and non-stationary time series analysis* Proc. R. Soc. Lond. A (1998) 455, 903:?995.

[3] Hui Li, Yuping Zhang and Haiqi Zheng *Hilbert-Huang transform and marginal spectrum for detecting and diagnosis of localized defects in roller bearings* Journal of Mechanical Technology, 2007