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**A robust detector for rolling element bearing  
condition monitoring, based on the modulation  
signal bispectrum, and its performance  
evaluation against the kurtogram**

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**Pro Vice-Chancellor for Research and Enterprise**

**&**

**Director of The Centre for Efficiency and Performance Engineering**

- 1. Introduction**
- 2. The modulation signal based detector**
- 3. Simulation study**
- 4. Application case studies**
- 5. Conclusions**

# 1. Introduction

- Bearings are at the heart of almost every rotating machine
  - they have **received a lot of attention** in the field of vibration analysis
  - because they are **common sources of machine faults**
- To keep machinery **operating reliably** many methods for bearing fault detection and diagnosis have been developed
  - **vibration measurement and associated signal processing** are the most widely used approach



## A review of signal processing methods

- High frequency resonance technique
- Cyclostationary spectral analysis
- Cepstrum analysis
- Bispectrum analysis
- Time-frequency analysis
- Self-adaptive noise cancellation
- Minimum entropy deconvolution
- Empirical mode decomposition

Most methods are based on tracking the **amplitude variations** of characteristic fault frequencies

Only limited attention has been given to utilisation of **modulation characteristics** in extracting the diagnostic information

But the Modulation Signal Bispectrum can be used to extract fault features from **envelope signals** giving reliable bearing fault detection, diagnosis and severity assessment

## Purpose of the research

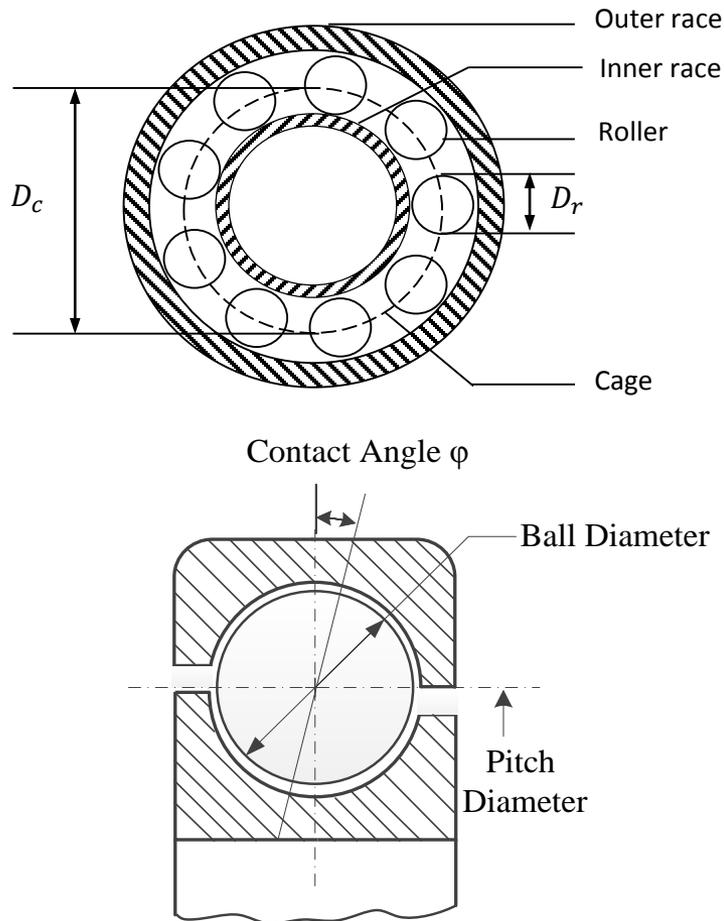
- To develop and evaluate a **robust detector** for bearing fault diagnosis based on **modulation signal bispectrum** (MSB) analysis

## The modulation signal bispectrum

- MSB analysis can be used to suppress **random noise** and to decompose **nonlinear modulation components** in a measured signal, eg vibration
- Advantages of the modulation signal bispectrum include:
  - 1) Highly effective suppression of random noise
  - 2) Revelation of the weak nonlinear characteristics of signals

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## Bearing fault frequencies



Outer race fault frequency:

$$BPFO = \frac{N_r}{2} F_s \left(1 - \frac{D_r}{D_c} \cos \phi\right)$$

Inner race fault frequency:

$$BPFI = \frac{N_r}{2} F_s \left(1 + \frac{D_r}{D_c} \cos \phi\right)$$

Ball fault frequency:

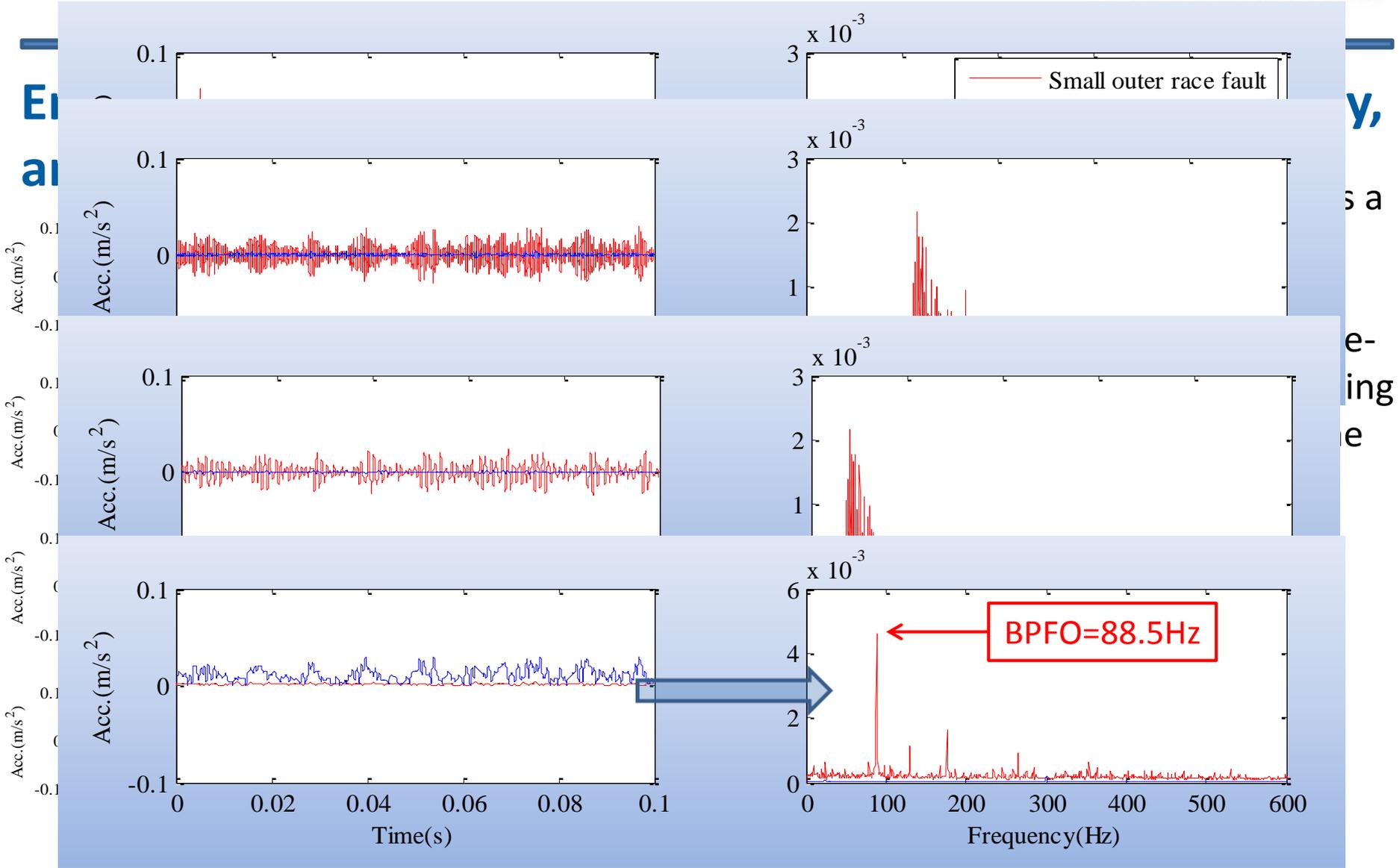
$$BSF = \frac{D_c F_s}{2D_r} \left(1 - \frac{D_r^2}{D_c^2} \cos^2 \phi\right)$$

Cage fault frequency

(often called the fundamental train frequency):

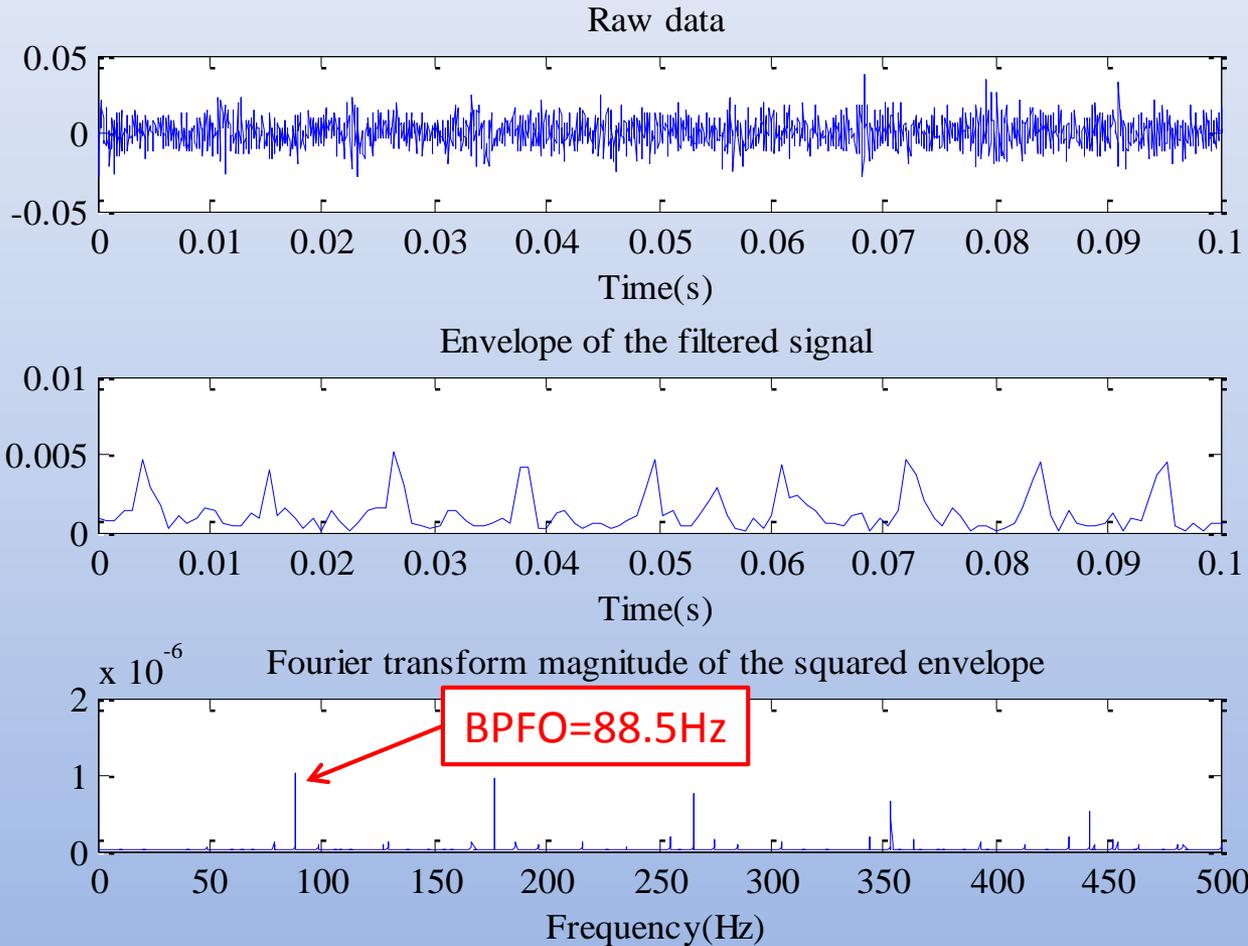
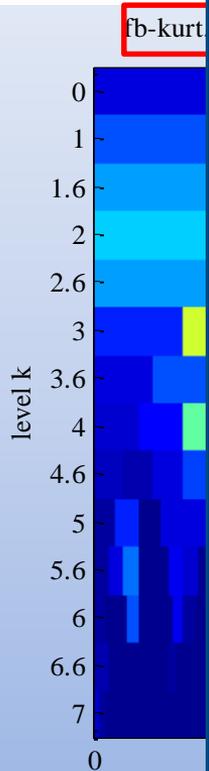
$$FTF = \frac{1}{2} F_s \left(1 - \frac{D_r}{D_c} \cos \phi\right)$$

# 2. The modulation signal based detector



# 2. The modulation signal based detector

## The kurtosis monitor



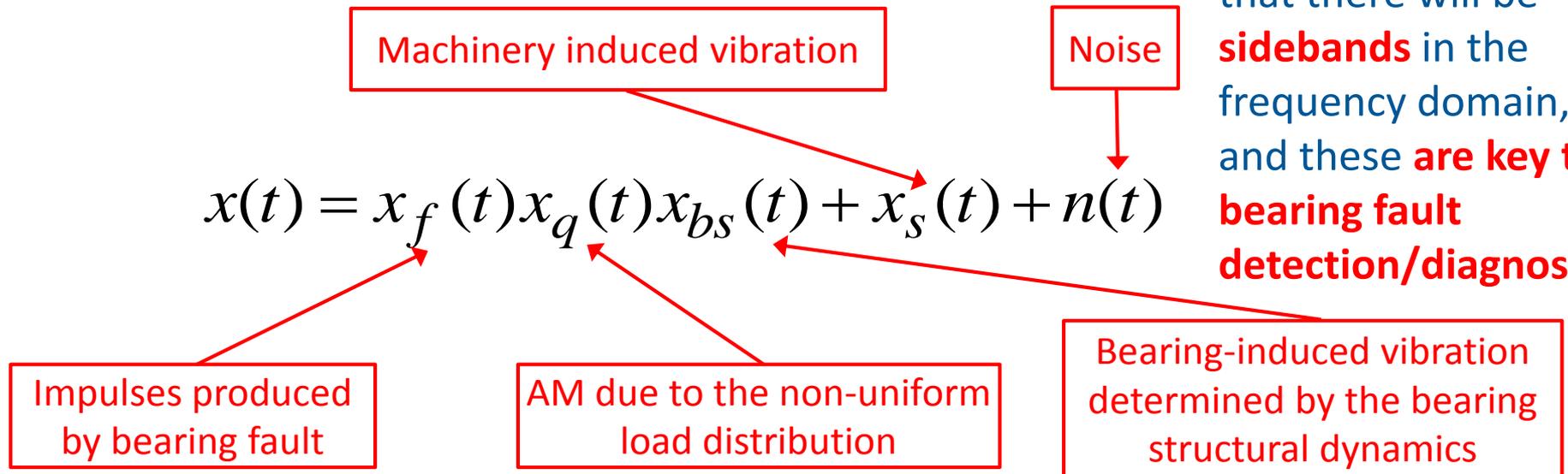
map of frequency regions filter  
level 4 filter  
filter

## The bearing vibration model

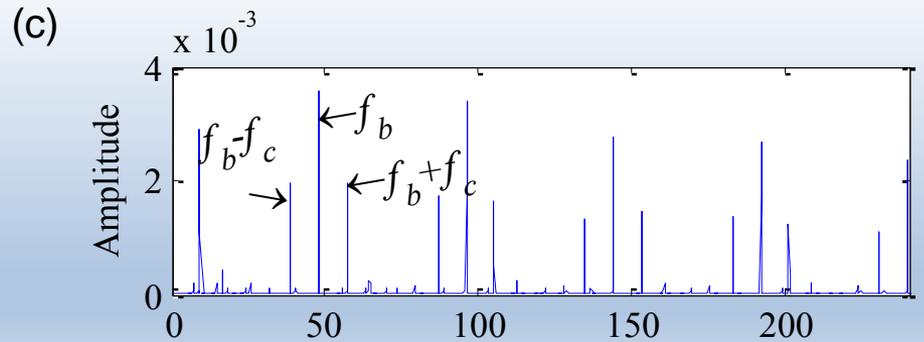
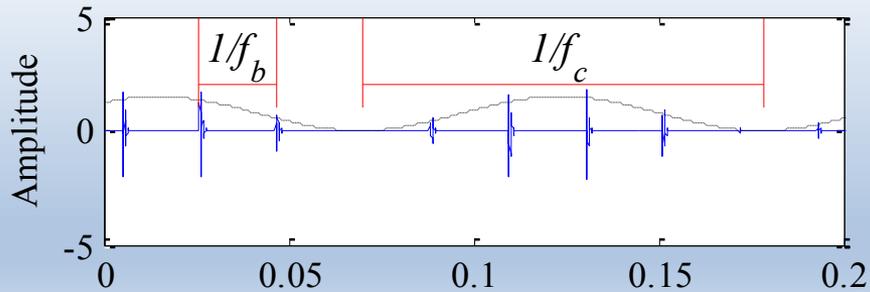
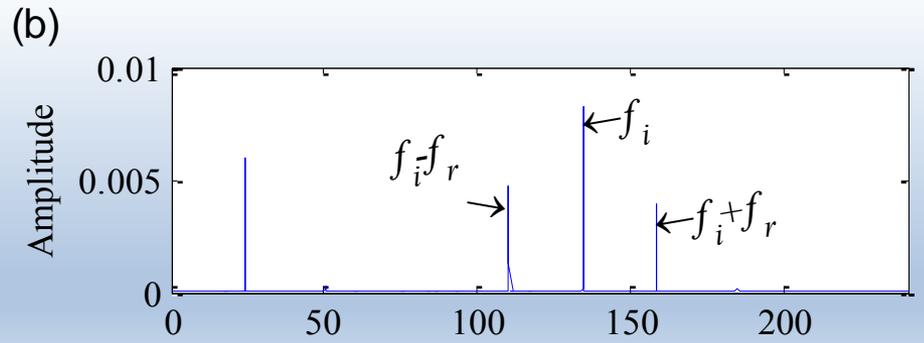
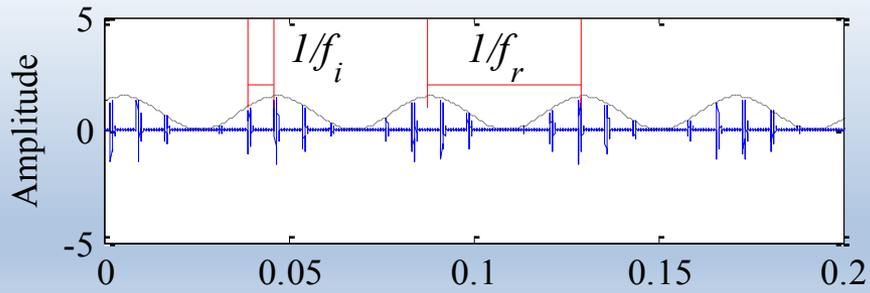
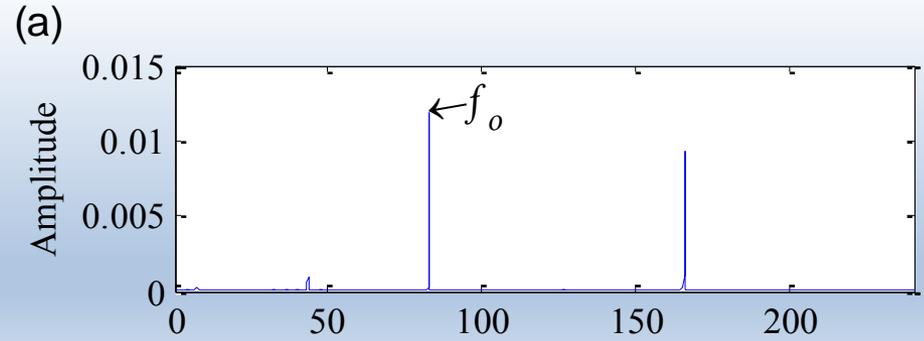
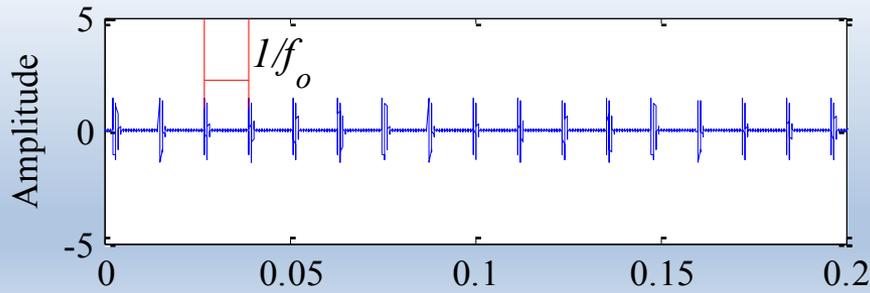
It was decided to use 2 ways of evaluating the new method: via simulated data and real data. To simulate bearing fault data, a bearing vibration model is needed.

The vibration signature  $x(t)$  of a faulty rolling element bearing is comprised of several components, and these are represented in the model as follows:

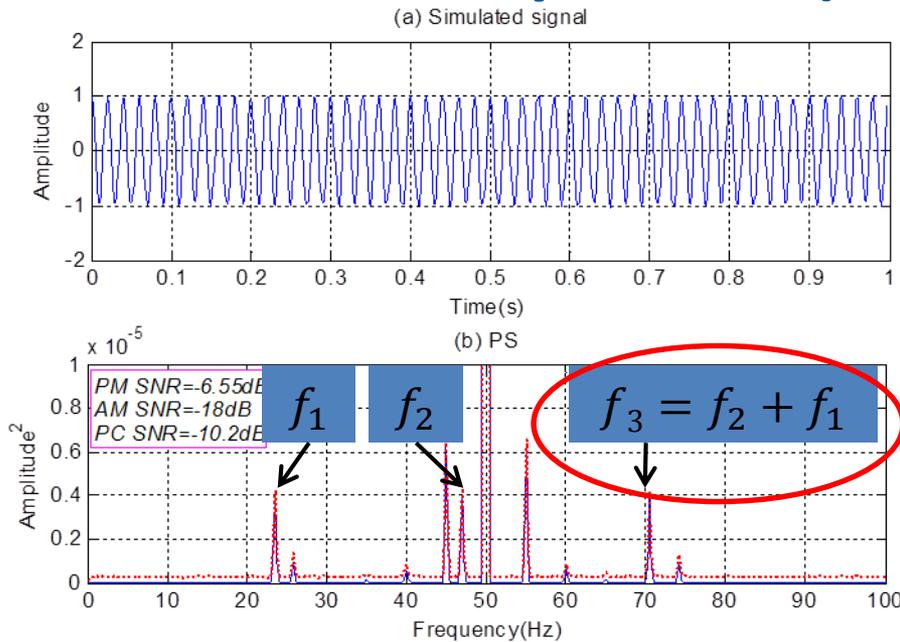
The presence of modulation in the time data means that there will be **sidebands** in the frequency domain, and these **are key to bearing fault detection/diagnosis**



# 2. The modulation signal based detector



## Conventional bispectrum (CB)



- Conventional bispectrum offers:
  - Nonlinear identification capability
  - Retention of phase information
  - Noise suppression capability

$$PS(f) = E\langle X(f)X^*(f) \rangle$$

Definition of CB:

$$B(f_1, f_2) = E\langle X(f_1)X(f_2)X^*(f_1 + f_2) \rangle$$

Phase of CB:

$$\varphi_{CB}(f_1, f_2) = \varphi(f_2) + \varphi(f_1) - \varphi(f_2 + f_1)$$

Coherence of CB:

$$b^2(f_1, f_2) = \frac{|B(f_1, f_2)|^2}{E\langle |X(f_1)X(f_2)|^2 \rangle E\langle |X(f_1 + f_2)|^2 \rangle}$$

$E\langle \rangle$  **An average must be performed to suppress random noise**

**But it is limited to  $f_1 + f_2 = f_3 \dots$   
...so it only shows the higher sideband**

### The modulation signal bispectrum (MSB)

The MSB is based on the CB, but is more attractive in this work because it contains both upper and lower sideband components

$$B_{MS}(f_c, f_x) = E \left\langle X(f_c + f_x) X(f_c - f_x) X^*(f_c) X^*(f_c) \right\rangle$$

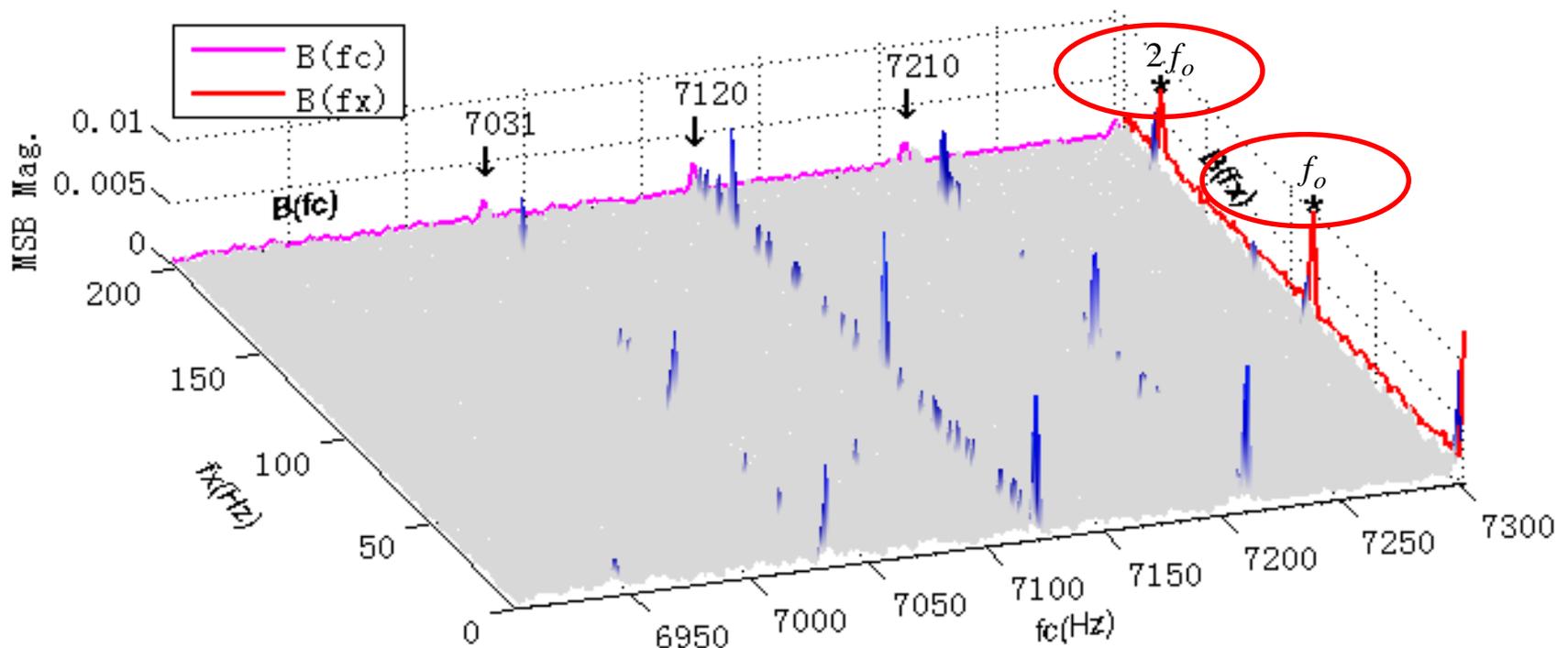
The MSB can itself be modified to enable precise quantification of sideband amplitudes, by removing the influence of the carrier frequency  $f_c$ . We call this the MSB sideband estimator (MSB-SE), defined as:

$$B_{MS}^{SE}(f_c, f_x) = \frac{B_{MS}(f_c, f_x)}{\sqrt{|B_{MS}(f_c, 0)|}}$$

The MSB-SE only includes the information of sidebands  $(f_c + f_x)$  &  $(f_c - f_x)$

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Typical results of the MSB detector -  $B(f_x)$  - formed from slices shown along  $B(f_c)$ , show that the optimal frequency band for detecting a bearing fault is at a specific value of  $f_c$ . Symptomatic features are labelled \*.



## 2. The modulation signal based detector

Vibration signal

Calculate the MSB using

Calculate the MSB-sideband estimator using

$$B^{SE}(f_c, f_x) = B_{MS}(f_c, f_x)$$

Calculate the compound MSB slice using

$$B(f_x) = \frac{1}{\sum N} \sum B^{SE}(f_c^k, f_x)$$

Calculate the robust MSB detector using

$$B(f_x) = \frac{1}{K} \sum_{k=1}^K B_{MS}^{SE}(f_c^k, f_x) \quad f_x > 0$$

Flow chart of the robust MSB detector calculation

# 3. Simulation study

## Four different simulation scenarios were developed

They use different levels of random noise and different amounts of aperiodic interference, to represent the noisy in-field measurements typically encountered in the vibration-based condition monitoring of rolling element bearings

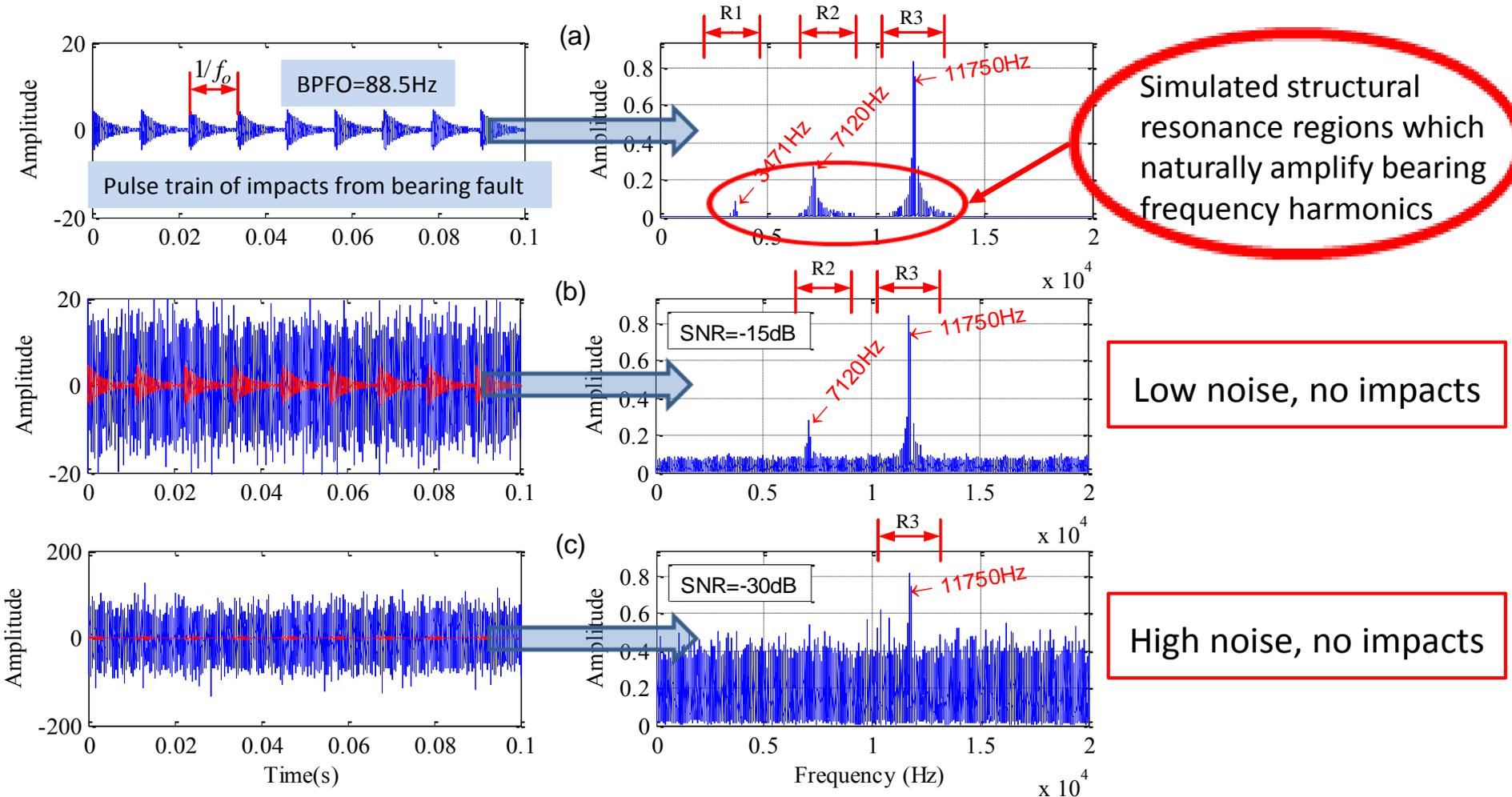
Scenario	White noise	Aperiodic impact interference	Type 1 SNR value	Type 2 SNR value
Low noise signal without impact interferences	Level 1	None	-15dB	n/a
High noise signal without impact interferences	Level 2	None	-30dB	n/a
Low noise signal with low level impact interferences	Level 1	Level 1	-15dB	-22dB
High noise signal with high level impact interferences	Level 1	Level 2	-22dB	-48dB

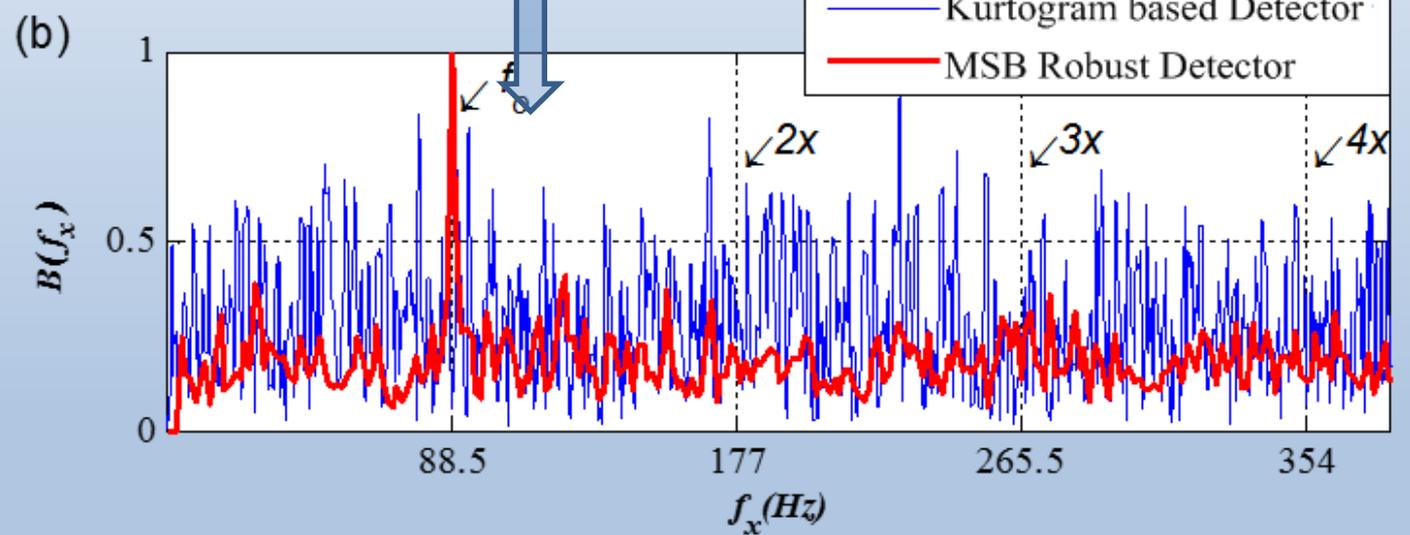
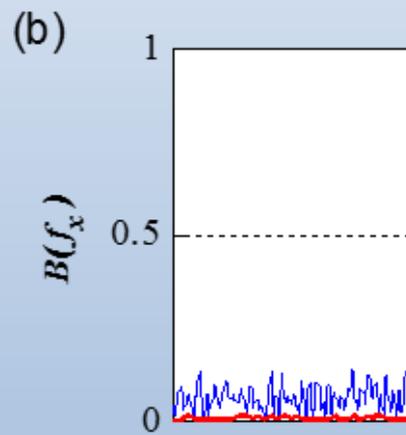
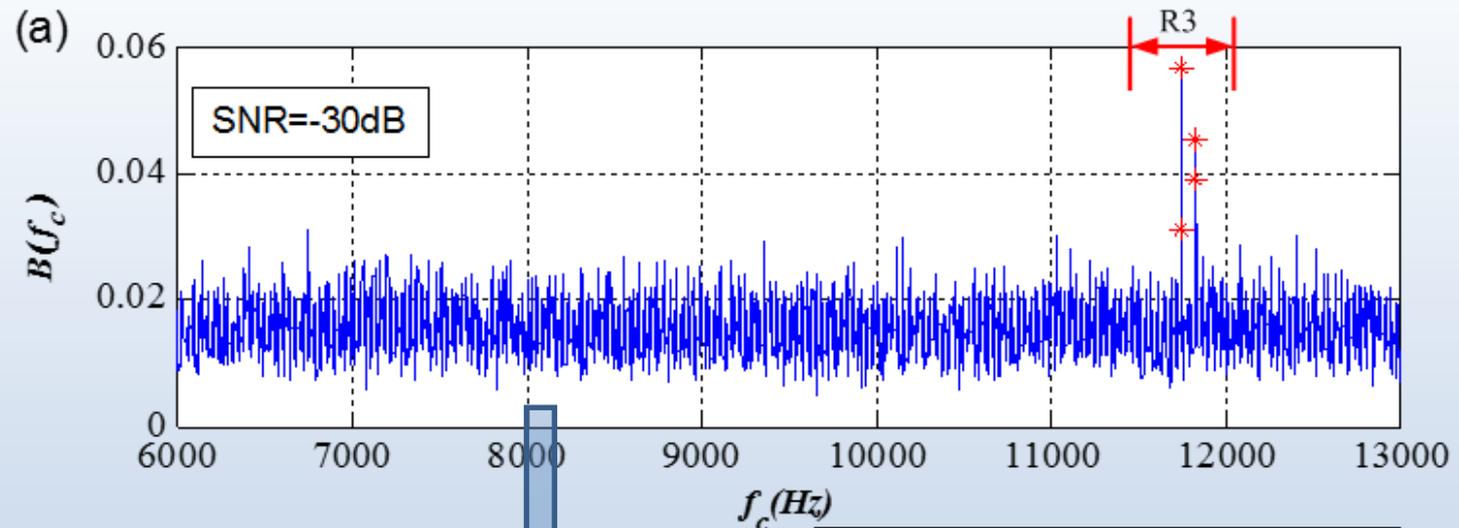
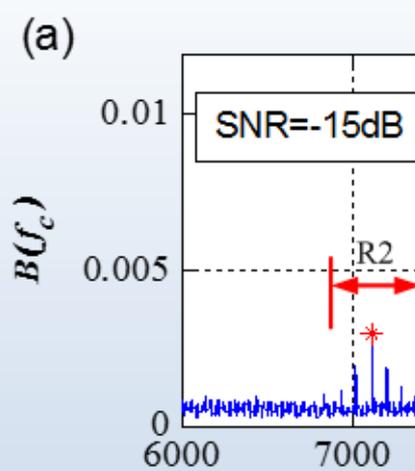
$$\text{Type 1 SNR} = 20\log_{10}\left(P_s / P_n\right)$$

$$\text{Type 2 SNR} = 20\log_{10}\left(A_s / A_n\right)$$

# 3. Simulation study

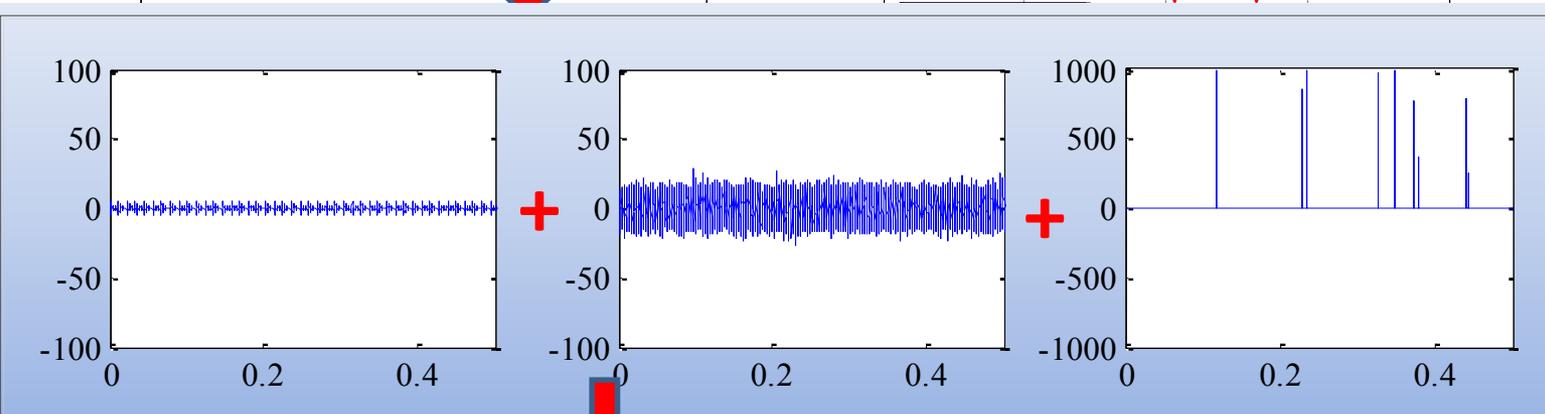
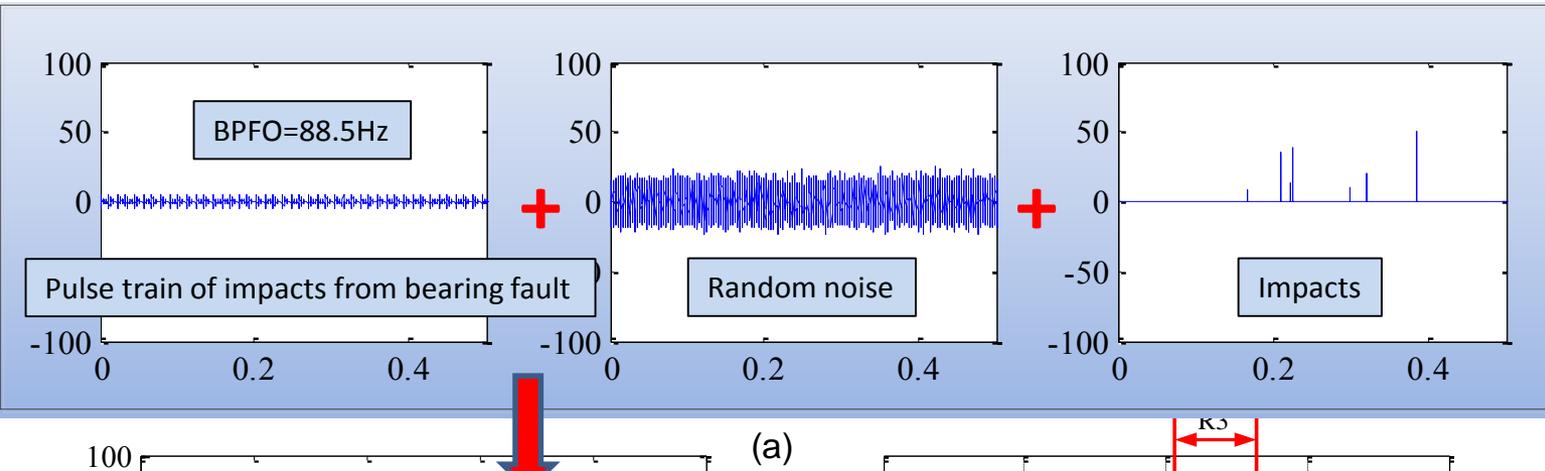
## The extent of white noise contamination



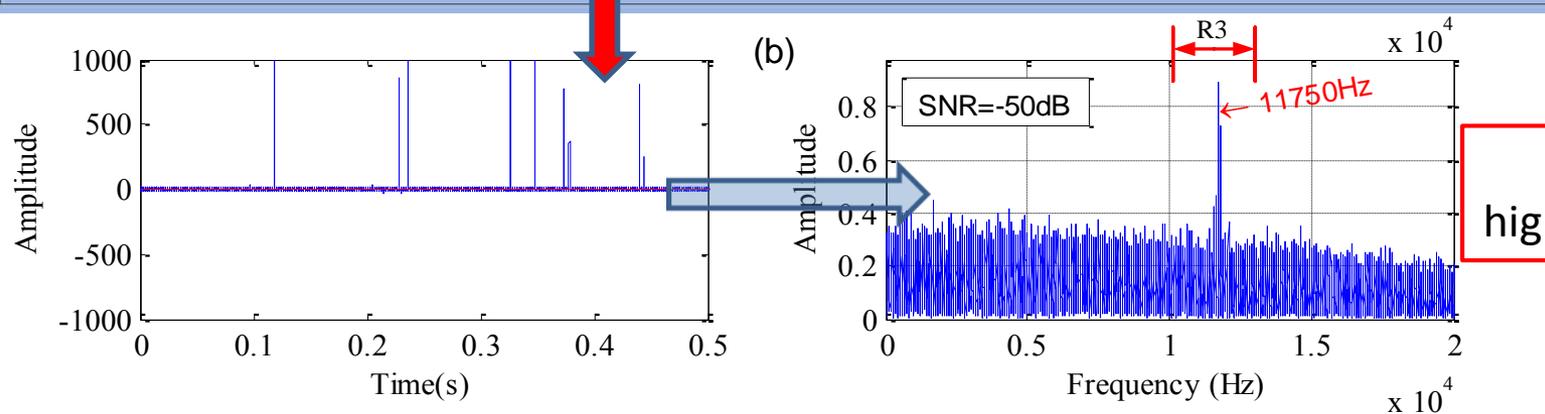


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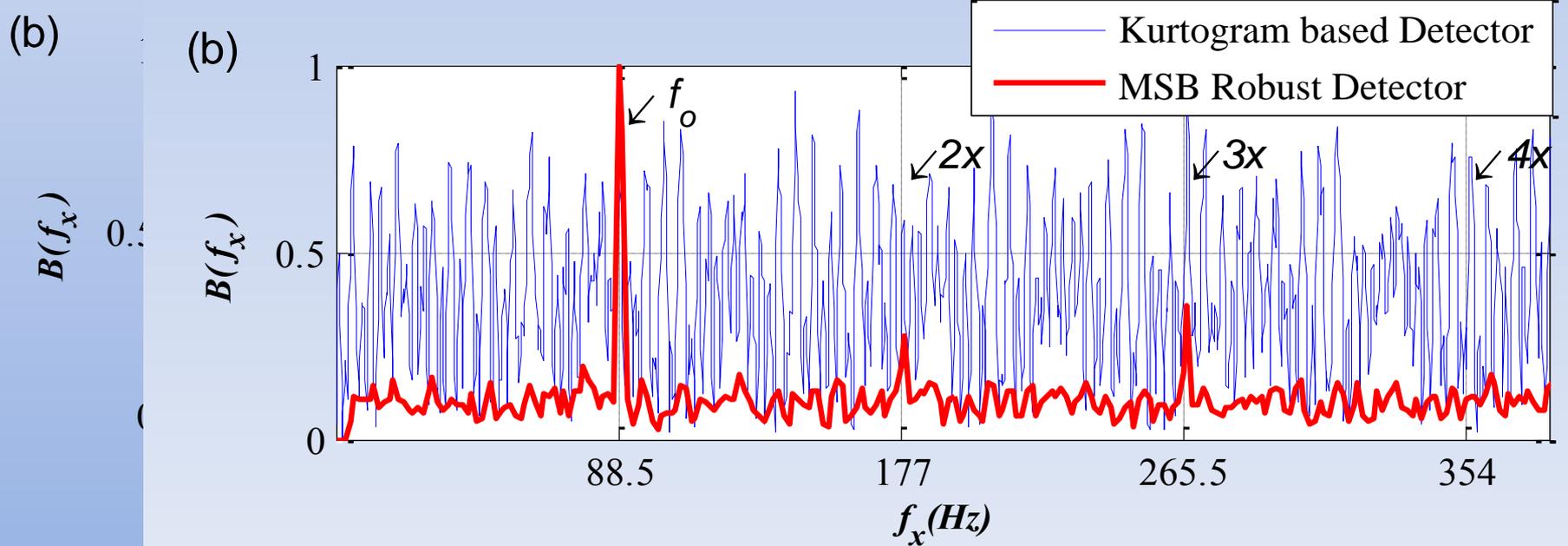
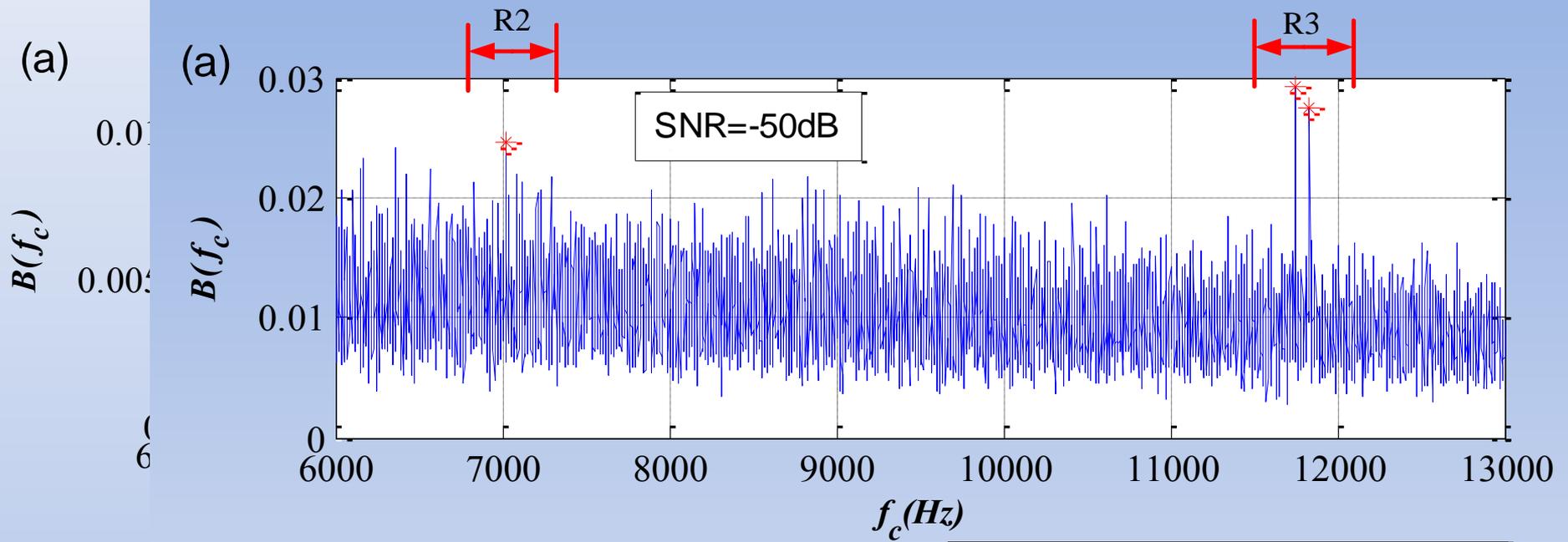
High noise, no impulses



Low noise,  
level impacts

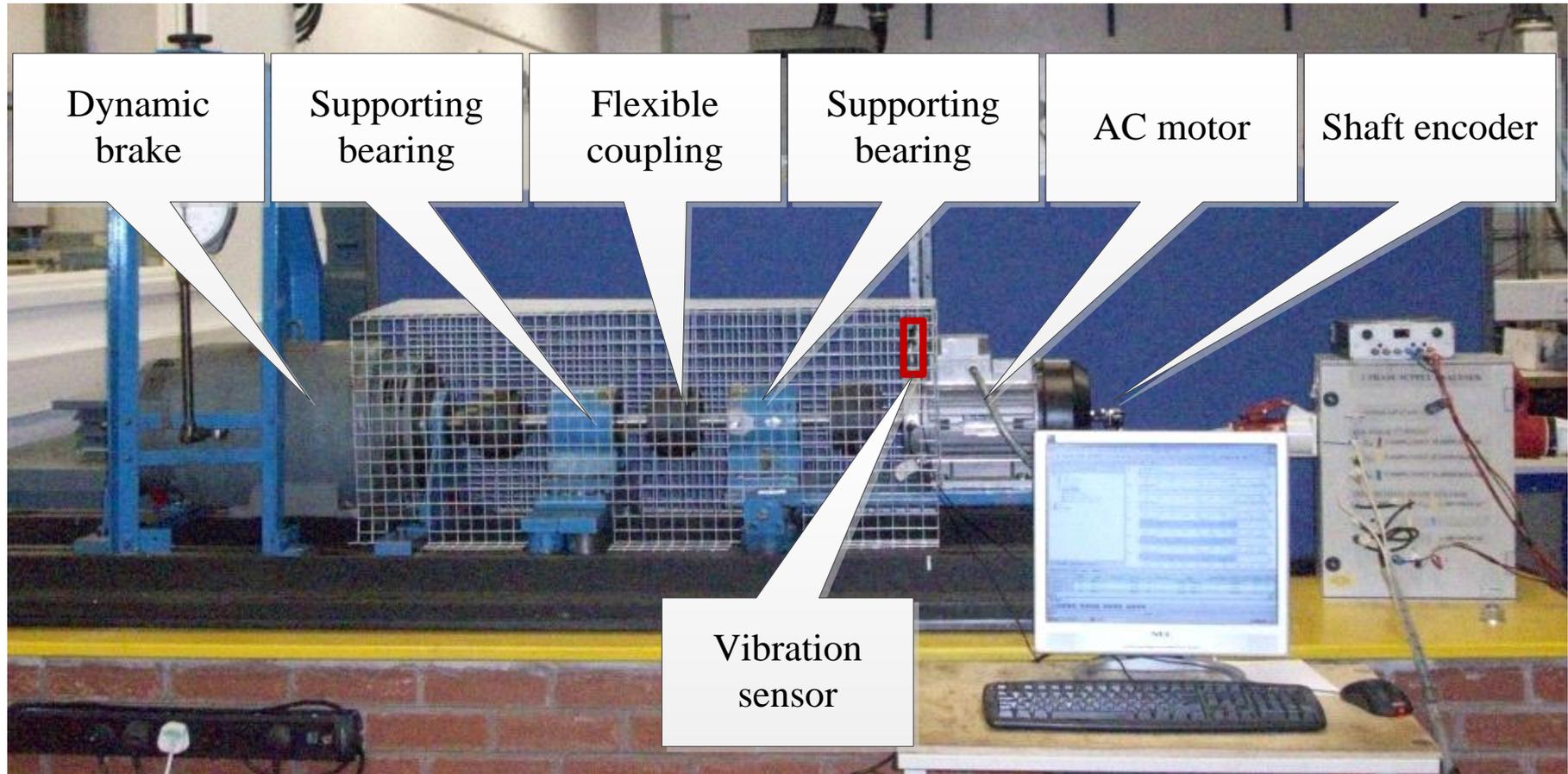


Low noise,  
high level impacts



# 4. Application case studies

## The first real application: motor bearing fault detection



# 4. Application case studies



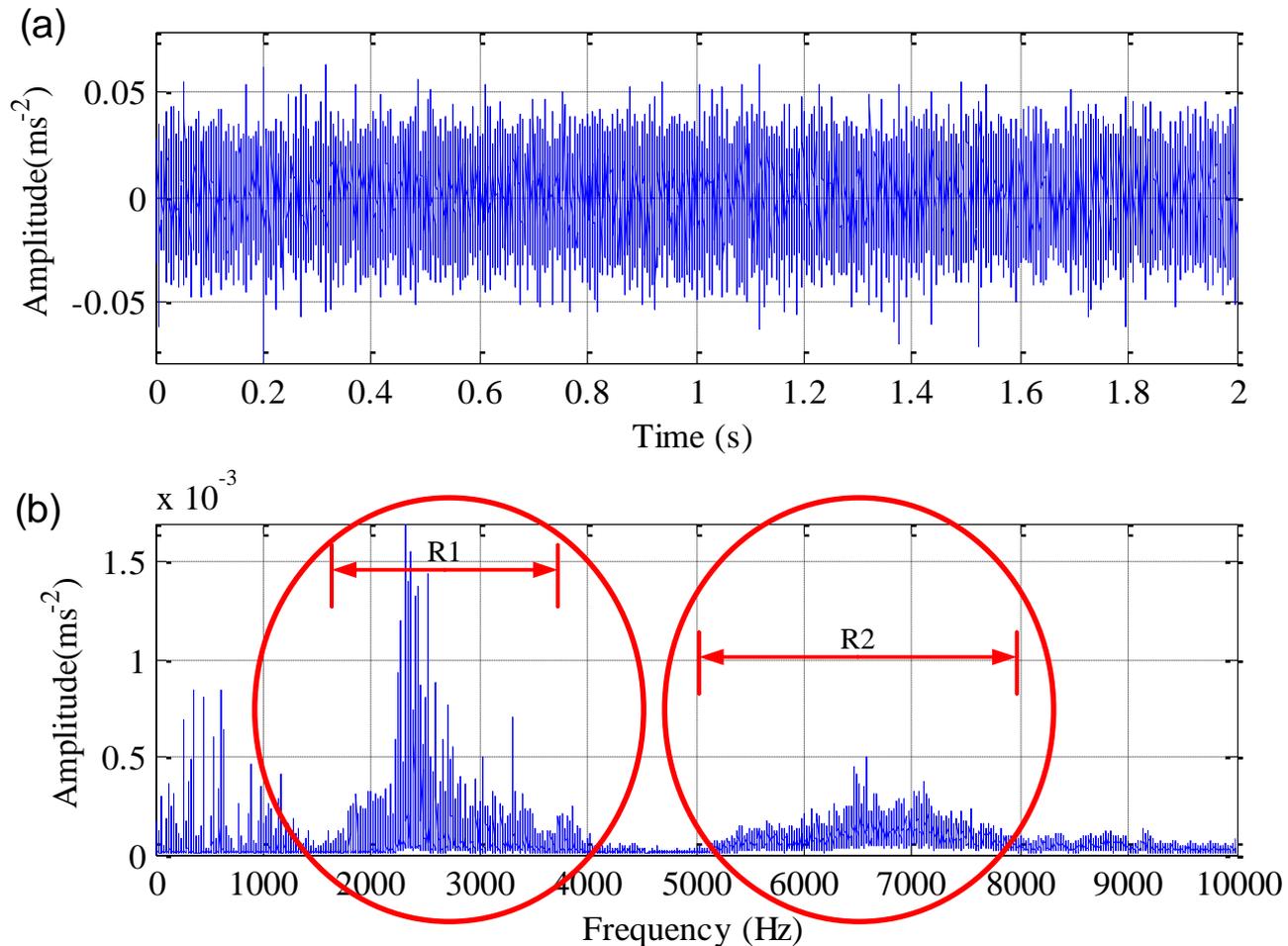
Electric motor bearing with a small seeded outer race fatigue defect (defect simulated by EDM)

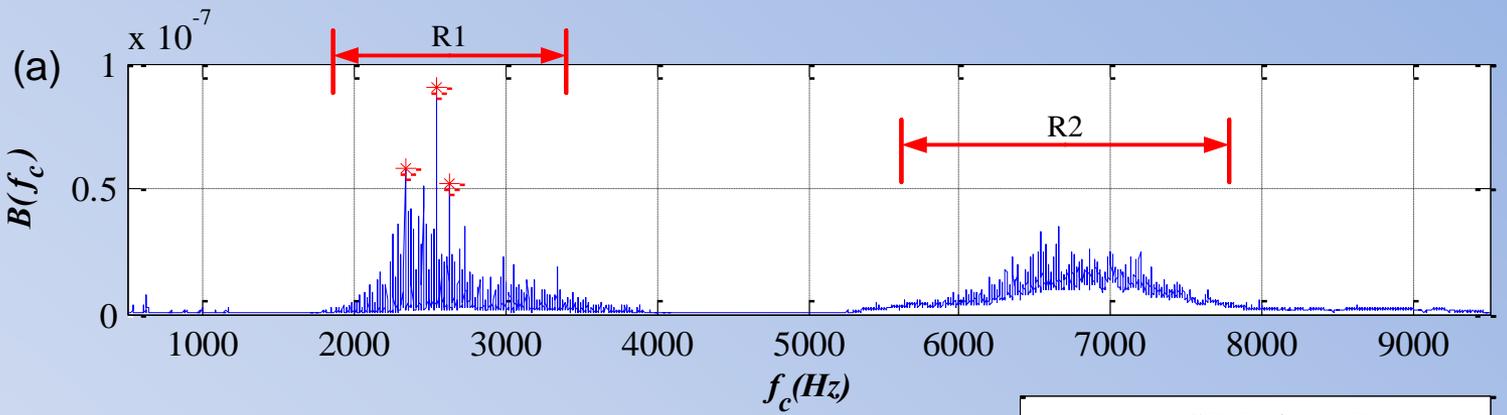
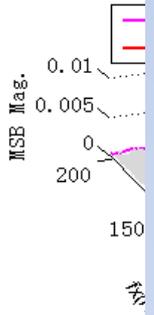
Specification of NSK Type 6206ZZ deep groove ball bearing

Parameter	Measurement
Pitch Diameter	46.4mm
Ball Diameter	9.53mm
Ball Number	9
Contact Angle	0°

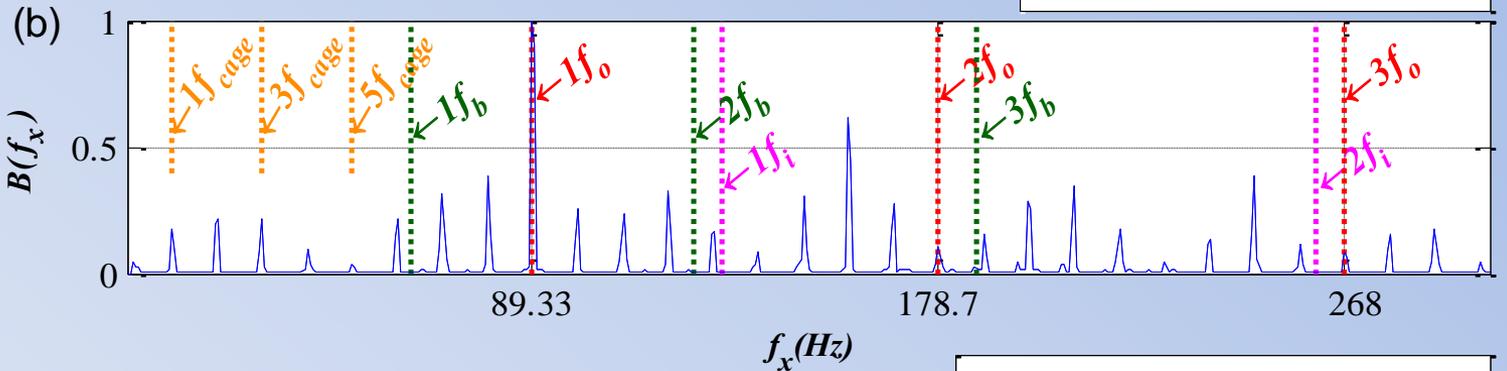
# 4. Application case studies

## The motor data reveals 2 clear resonant regions

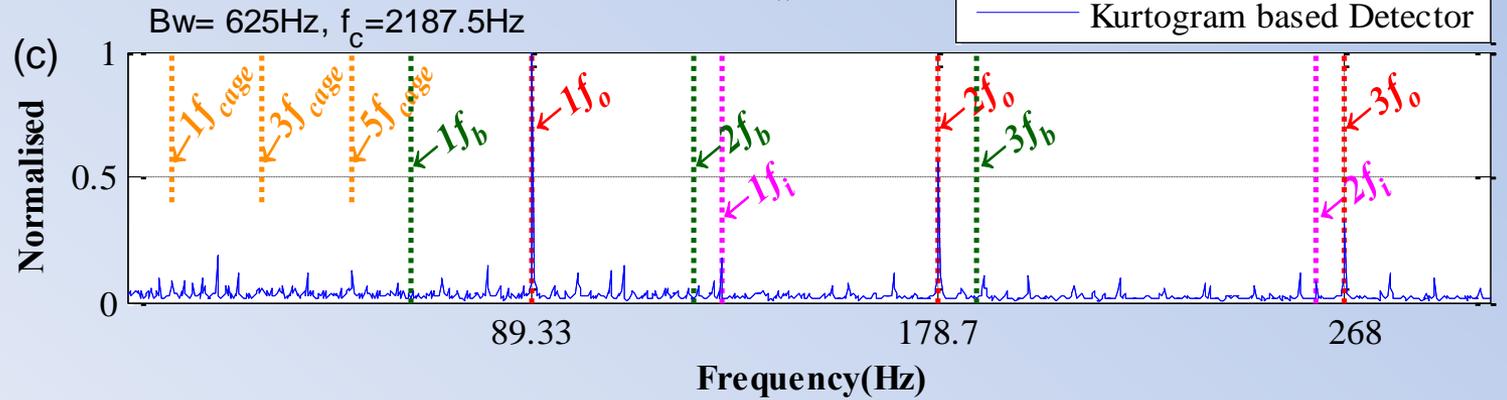




MSB Robust Detector

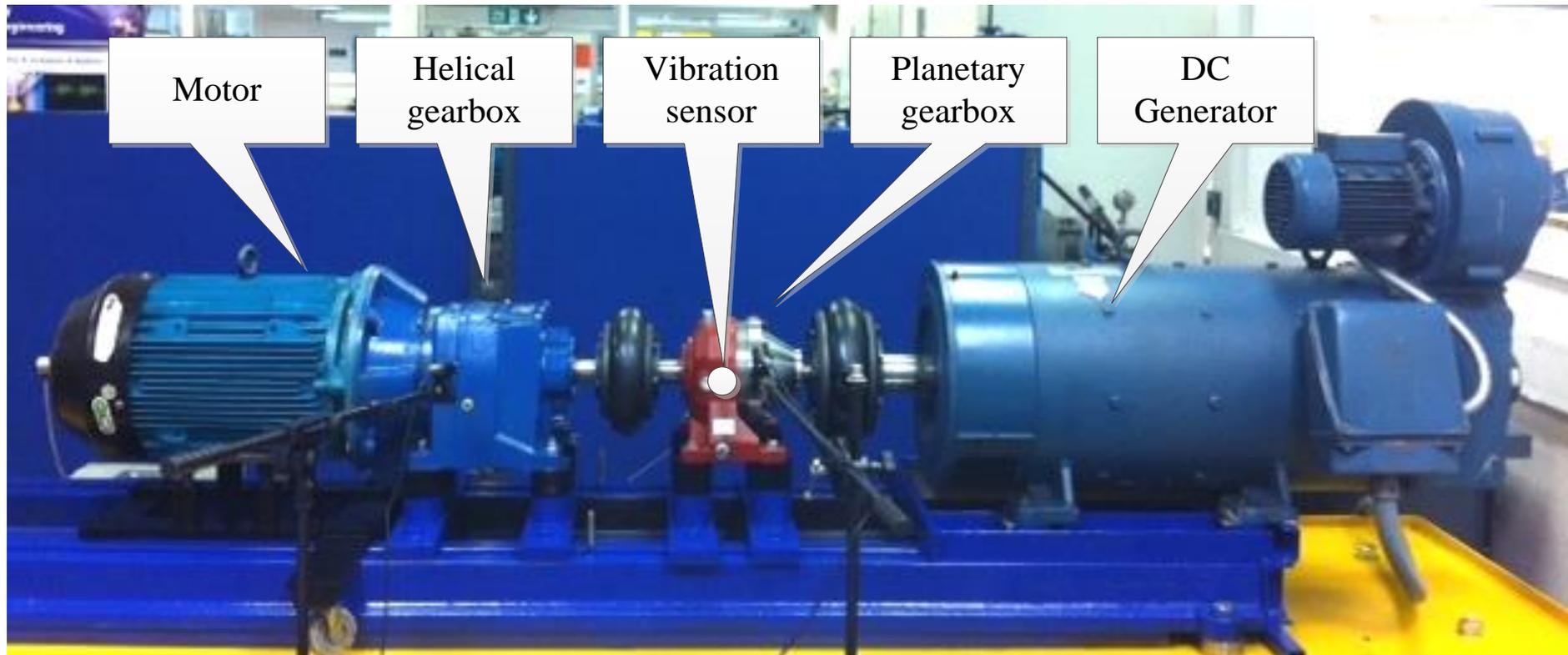


Kurtogram based Detector



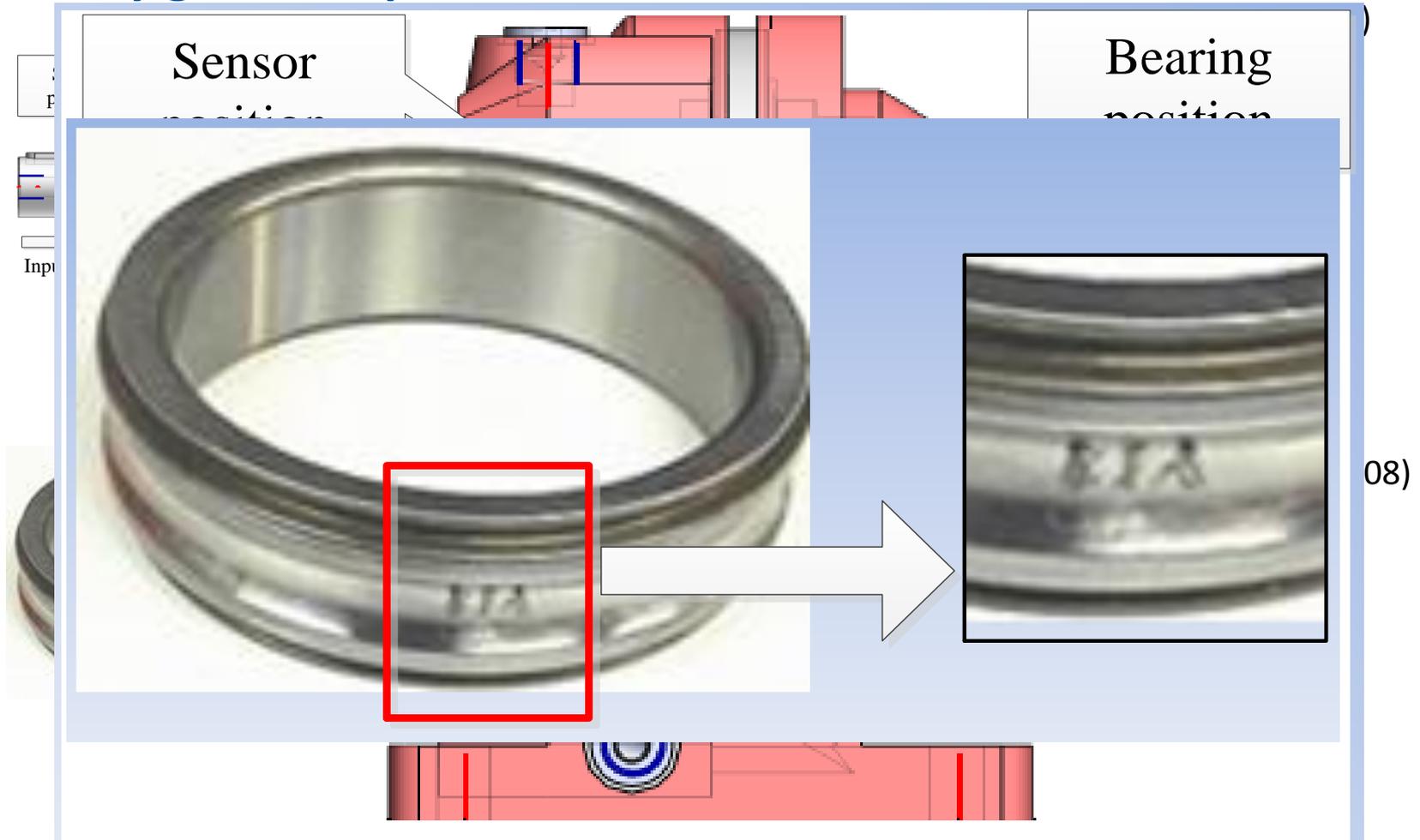
# 4. Application case studies

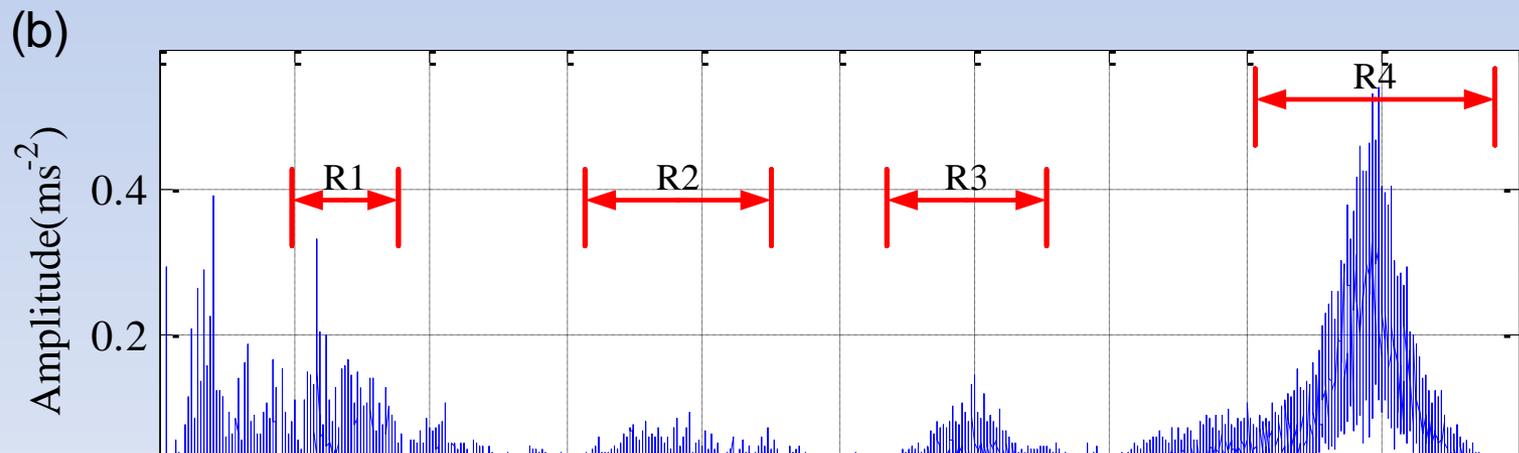
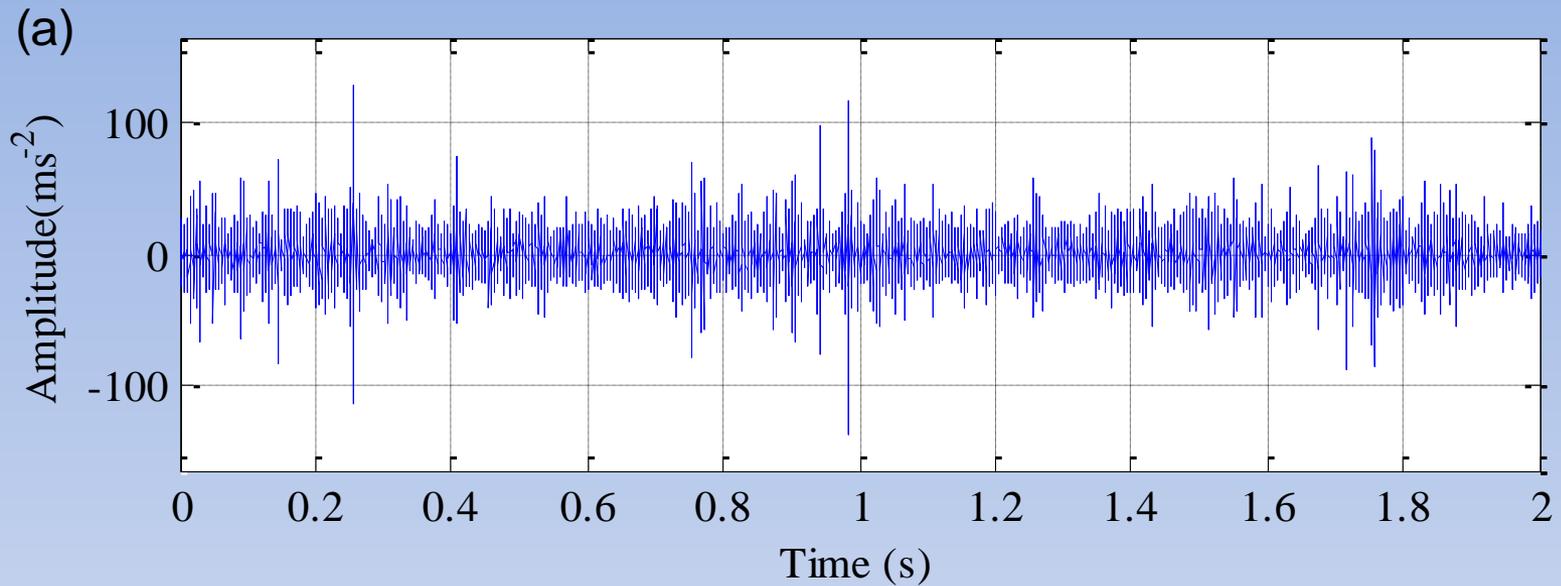
## The second real application - planetary gearbox bearing fault detection



# 4. Application case studies

## Planetary gearbox specification

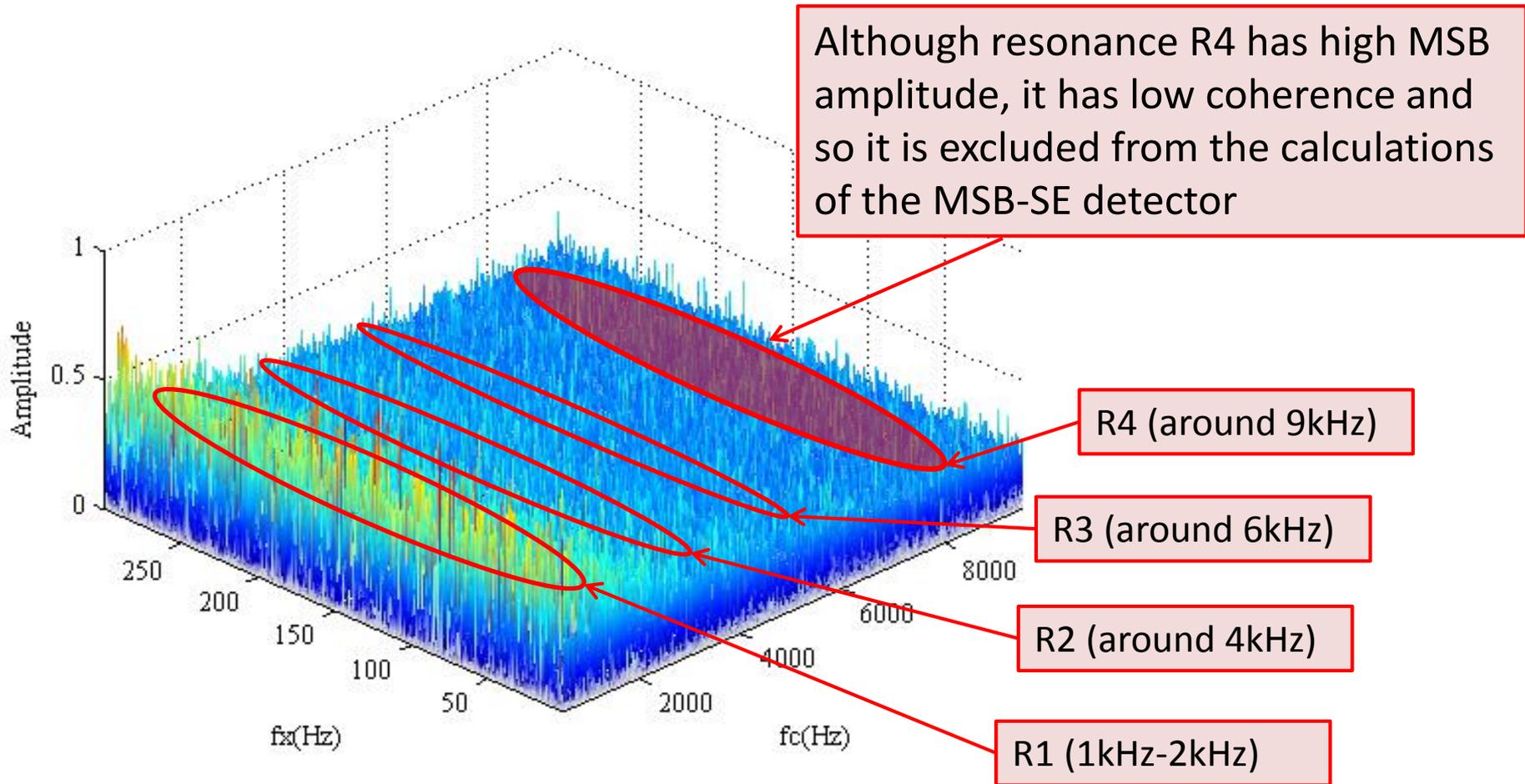




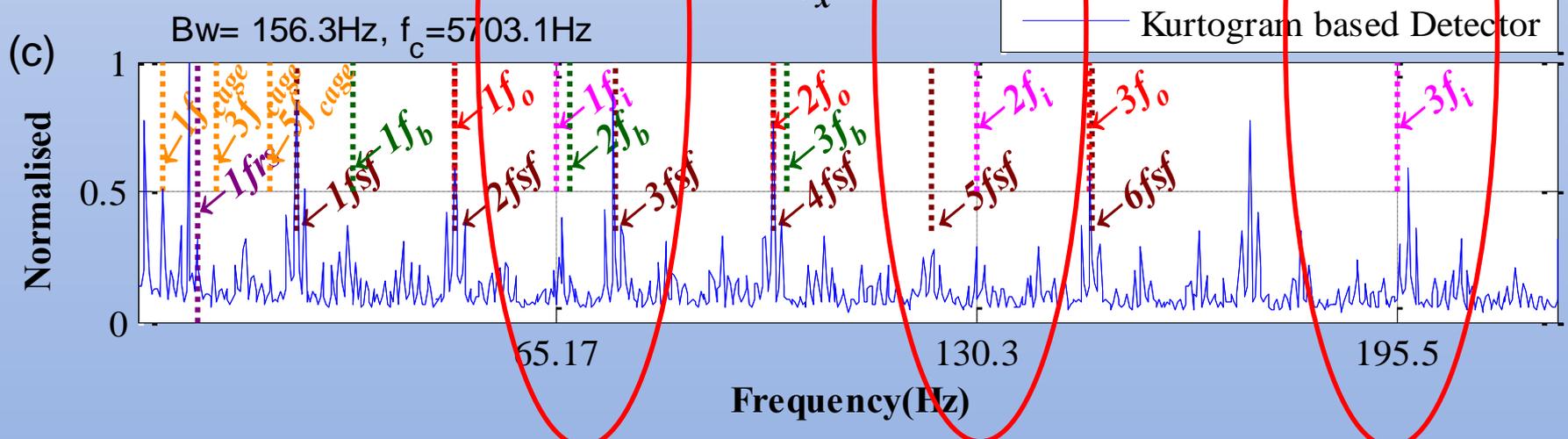
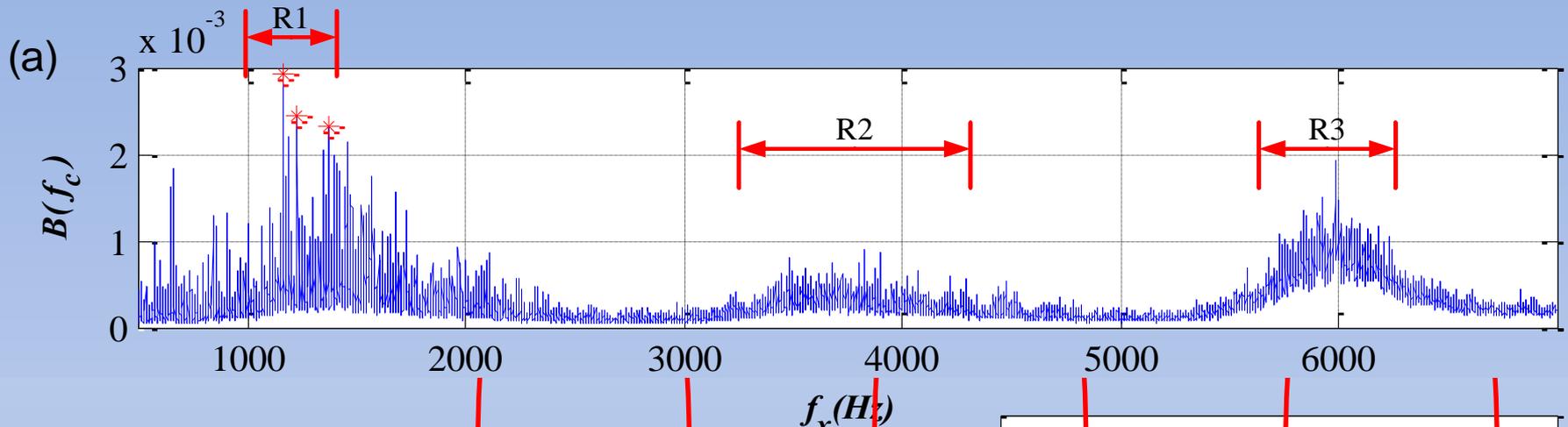
But when choosing the resonant region(s) to use in the calculation of the MSB-SE, it is always wise to check the coherence...

# 4. Application case studies

## MSB-SE coherence for the planetary gearbox



# 4. Application case studies



# Conclusions

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- The MSB is demonstrably effective in suppressing noise and decomposing the nonlinear modulation components
  - The MSB-SE is effective in the suppression of both **stationary** white noise and **aperiodic** impact impulses.
- Simulated signal and real data studies shows that the capability of the MSB-SE exceeds that of a kurtogram-based detector.
- The application to signals from a planetary gearbox shows that the new approach can successfully detect bearing faults in circumstances where no other method is able to do so.