Chapter 4

Fractional Hilbert Transform Based Enveloping Techniques

'Probability fractions arise from our knowledge and from our ignorance.'

-Ian Hacking

The concept of fractions has always intrigued the human mind. It has been instrumental to our understanding of the number systems and intricacy of the notion of infinity. The focus of this chapter is on the generalisation of signal enveloping in fractional domain to enhance bearing fault features.

Highlights:

- In this chapter, an analysis of fractional Hilbert transform based enveloping methods is carried out.
- Fractional Fourier transform based fractional enveloping method is selected as an appropriate method based on kurtosis and spectral feature maximisation.
- With a comparative analysis of three representative cases using existing signal processing methods with proposed fractional enveloping, it is shown that the spectral feature values are significantly improved.

Fractional calculus is correctly termed as a "laboratory for special functions and integral transforms" [170]. Fractional domain processing provides a generalization of existing concepts, which can be explored for obtaining optimum features in many engineering applications. Such applications include, but are not limited to,

- Modelling of dynamic systems,
- Optimal control of systems,
- Understanding electrical, mechanical and thermal properties of materials,
- Biomedical applications and
- Signal and image processing applications.

For diagnosis of bearing faults, this research is riveted around the signal processing aspects of fractional calculus, which consists of generalizations of well-established integral transforms, like Fourier transform (FT) and Hilbert transform (HT). A brief study on the use of fractional Hilbert transform to find fractional envelopes of bearing signals was performed in [111]. The application of fractional envelope method is yet to be explored in detail for bearing fault diagnosis, but it is well-established as a signal processing tool [171–174]. In these early papers on fractional transforms, the fractional Fourier transform (FrFT) and fractional Hilbert transform (FrHT), were shown to be useful for edge detection. In particular, it was proved with example, that for different values of the fractional parameter different edges can be enhanced using FrHT. This was called as selective or localized edge enhancement, which was later proved mathematically in [175]. In bearing fault diagnosis, the impulsive nature of bearing signal is to be detected and thus FrHT can be used for this application.

4.1 Theoretical Background

4.1.1 Hilbert Transform

Hilbert transform (HT) is an efficient tool to calculate the signal envelope and has been extensively used for bearing fault diagnosis. Enveloping demodulates the signal and helps in extracting the low-range bearing fault characteristic frequencies from high-frequency resonance. It is often performed after band-pass filtering (or signal decomposition) and is followed by finding the envelope spectrum. Bearing fault signature is complexly modulated due to various machine components interacting with each other and, thus, signal envelope often reveals critical diagnostic information. But, due to noise and other interferences, bearing fault signatures are, sometimes, suppressed. Fractional enveloping (FrE) can be used in such cases to selectively enhance the impulsive nature of bearing fault signatures.

Conventional signal envelopes are calculated as the magnitude of an analytic signal - a complex signal with real part as the signal itself and the imaginary part as the Hilbert transform of the signal. The Hilbert transform $(\tilde{x}(t))$ of a signal $(x(t))$ is defined by following integral -

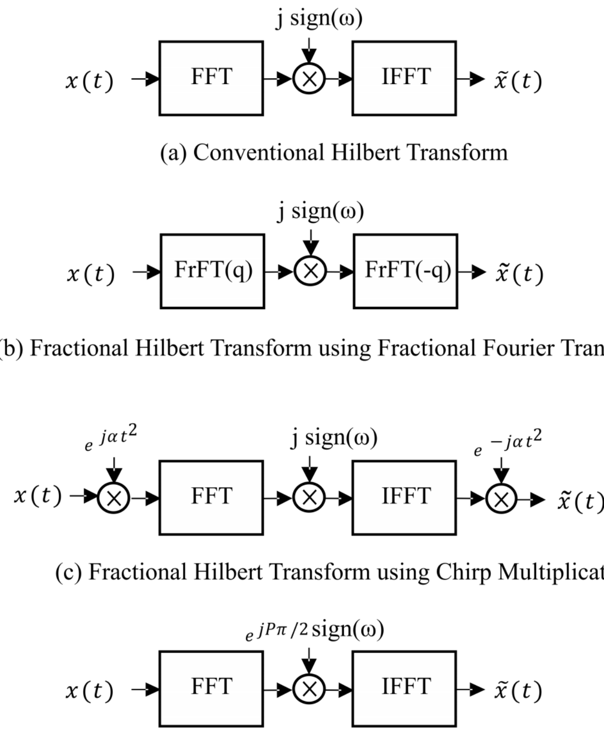
$$\tilde{x}(t) = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau \tag{4.1}$$

and the corresponding analytic signal (x_a) and signal envelope (x_e) are -

$$x_a(t) = x(t) + j\tilde{x}(t),\ x_e(t) = |x_a(t)| \tag{4.2}$$

Eq. 4.1 is calculated as a Cauchy principle value. Implementation of this transform is, however, simple because of its frequency domain transfer function given by -

$$\tilde{X}(\omega) = \begin{cases} -j, \omega > 0 \\ 0 \quad , \omega = 0 \\ +j, \omega < 0 \end{cases} \tag{4.3}$$



(a) Conventional Hilbert Transform

(b) Fractional Hilbert Transform using Fractional Fourier Transform

(c) Fractional Hilbert Transform using Chirp Multiplication

(d) Fractional Hilbert Transform using Modified Hilbert Filter

Figure 4.1: Block diagram of conventional Hilbert transform and its generalisations (sign-signum function, FFT-fast Fourier transform, IFFT-inverse fast Fourier transform, FrFT-fractional Fourier transform, IFrFT-inverse fractional Fourier transform)

4.1.2 Fractional Enveloping

Fractional Hilbert transform is a generalisation of conventional Hilbert transform and in literature, following methods are found -

- Fractional Fourier Transform (FrFT) [173, 174],
- Modified Hilbert Filter (MHF) [173, 174],
- Chirp Multiplication (CM) [176]

The block diagrams for these methods are shown in Fig. 4.1 and they are explained in detail in following subsections.

Fractional Fourier Transform (FrFT):

Fractional Fourier transform (FrFT) is a generalisation of Fourier transform [177]. In time-frequency representation, Fourier transform can be seen as a rotation by $\pi/2$ rad, whereas FrFT can be seen as rotation by a fractional angle $q = Q\pi/2$. For $Q = 0$, the FrFT operation produces the original signal itself, while for $Q = 1$, it returns the Fourier transform of the signal. Also, subsequent application of FrFT with fractional parameters Q_1 and Q_2, gives the combined effect of FrFT with fractional parameter $Q_3 = Q_1 + Q_2$. If the fractional angle q is not a multiple of 2π, then the FrFT kernel is given as -

$$K_q(t,u) = \sqrt{\frac{1 - j\cot q}{2\pi}} e^{(j \ \frac{t^2+u^2}{2} \ \cot q - j \ u \ t \ \mathrm{cosec} q)} \tag{4.4}$$

If q is a multiple of 2π, then the kernel is simply $\delta(t-u)$ and if $(q+2\pi)$ is a multiple of 2π, then it is $\delta(t+u)$. There are various algorithms to implement the FrFT and its discrete version [178]. We use a fast computation of the FRFT as proposed by Tao et al. [179].

Modified Hilbert Filter (MHF):

Generalized quadrature filter (GQF) is a generalization of Eq. 4.3, and is defined in frequency domain as -

$$\tilde{X}_p(\omega) = \begin{cases} e^{-jp\pi/2}, \omega > 0 \\ 0 \qquad\quad, \omega = 0 \\ e^{+jp\pi/2}, \omega < 0 \end{cases} \tag{4.5}$$

Thus, the conventional Hilbert transform is a special case of this at $p = 1$. Application of this method is studied for bearing fault diagnosis in [111]. Although, the kurtosis values are found to improve in the fractional domain, this method does not help in improving the spectral fault features. The amplitudes of fault characteristic frequency (FCF) does not vary much in the fractional domain for this method.

Chirp Multiplication (CM):

This method calculates the generalisation of the Hilbert transform by multiplying it with chirp signals $e^{j\alpha t^2}$ and $e^{-j\alpha t^2}$. It provides a quicker way of obtaining the fractional Hilbert transform, as fractional Fourier transform takes longer time to calculate. In a way, this method bridges the gap between the earlier two methods, such that the performance is better than the modified Hilbert filter, whereas the speed is better than the fractional Fourier transform.

4.2 Selection of Fractional Enveloping Method

4.2.1 Kurtosis Maximisation

Kurtosis is conventionally used as an indicator of bearing fault. A bearing fault signature is typically impulsive in nature because of the high frequency resonance due to presence of fault. Larger values of kurtosis indicates presence of fault in the bearing. Thus an appropriate fractional enveloping method is chosen based on its ability to maximise the kurtosis value in the fractional domain. The fractional envelopes are calculated for discrete values of 0 to 1 with an increment of 0.1.

Fig. 4.2 shows the maximum kurtosis values of CWRU-2013 data cases obtained using the available fractional enveloping methods. The important observations from the figure are -

1. The kurtosis values for healthy cases are significantly low compared to the faulty cases. However, these values are not sufficient for classification.
2. The fractional Fourier transform (FrFT) method has larger values of kurtosis compared to other methods for faulty cases. This means that the FrFT method is sensitive to the impulsive or faulty nature of the signal.

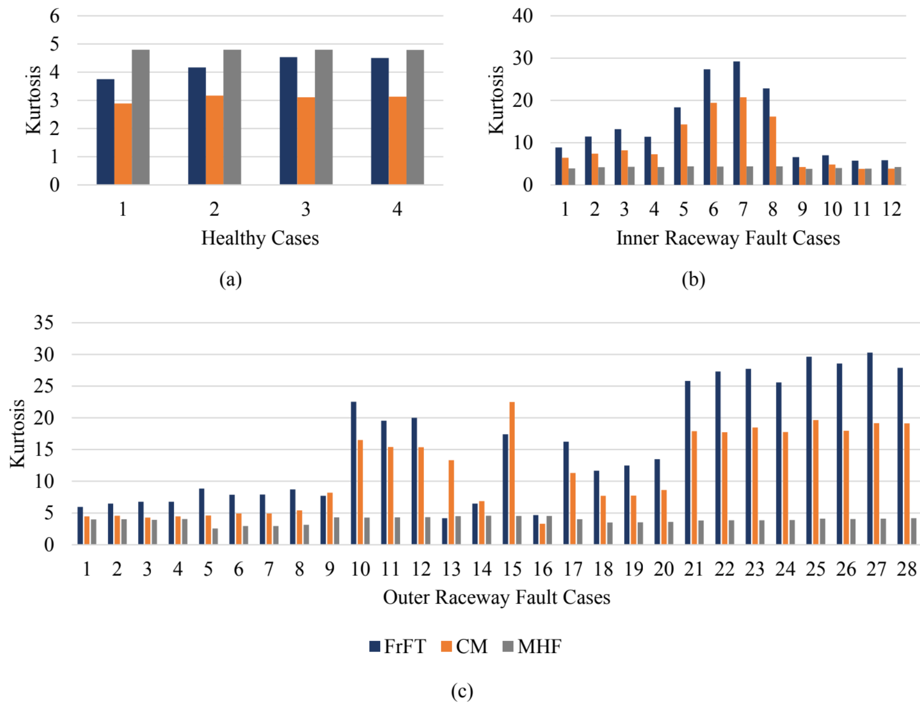


Figure 4.2: Comparison of fractional enveloping methods for maximum kurtosis. Dataset : CWRU-2013 (primary accelerometer data) (a) Healthy cases, (b) Inner Raceway Faults, (c) Outer Raceway Faults (FrFT - Fractional Fourier Transform, CM - Chirp Multiplication, MHF - Modified Hilbert Filter)

4.2.2 Spectral Feature Maximisation

As shown earlier the kurtosis can be maximised using the fractional envelope of the bearing signal. However, kurtosis alone is not enough to detect and identify the faults. Thus these signal processing methods are compared based on their performance to improve a spectral feature called the Squared Envelope Spectrum Feature (SES Feature) [135]. It is defined as -

$$\text{SES Feature} = \frac{1}{5}\,\Sigma_i(A_i - \mu), \quad i = 1,2,3,4,5 \tag{4.6}$$

-where A_is are the amplitudes of first 5 harmonics of the fault frequency and μ is the spectrum average. To get consistent values of SES Feature for comparison, the spectrums are scaled between 0 to 1. The fractional envelopes are calculated for discrete values of 0 to 1 with an increment of 0.1.

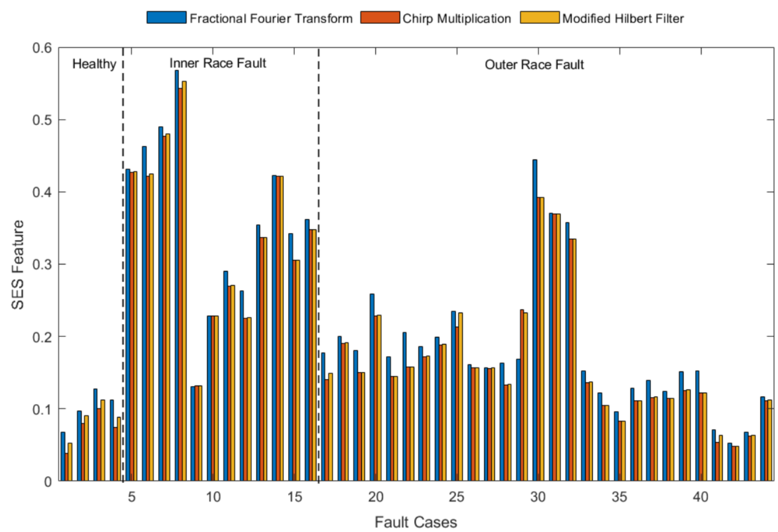


Figure 4.3: Comparison of fractional enveloping methods for SES feature maximisation. Dataset : CWRU-2013 (primary accelerometer data)

Fig. 4.3 shows the maximised SES features for CWRU-2013 dataset using fractional enveloping methods. The important observations from the figure are -

1. The SES feature values for healthy cases are significantly low compared to the faulty cases. However, these values are not sufficient for classification.
2. The fractional Fourier transform (FrFT) method has larger values of SES feature compared to other methods for faulty cases. This means that the FrFT method is sensitive to the kurtosis and SES feature values of the bearing signals.

A similar trend is observed for the CWRU-2013 data from secondary accelerometer. Thus FrFT based fractional enveloping is selected as appropriate method for bearing fault diagnosis. This method is further explored for enhancing the spectral fault features. In the upcoming sections, a comparative analysis of standard signal processing methods is carried out to highlight the improvement using the fractional enveloping.

4.3 Proposed Algorithm

In previous section, it is shown that two important fault features - kurtosis and the SES feature- can be maximised in the fractional domain. Although, fractional enveloping can help in improving the fault features, it can not filter out the unwanted noise in the signal. As discussed in previous chapters, the use of wavelet based filter-banks is a standard practice in the field. Thus to modify the conventional enveloping, it is proposed to use the fractional enveloping using fractional Fourier transform along with the discrete wavelet packet transform.

The proposed algorithm is thus based on fractional envelope using FrFT and maximal overlap discrete wavelet packet transform (MODWPT). Fig. 4.4 shows the block diagram of proposed algorithm.

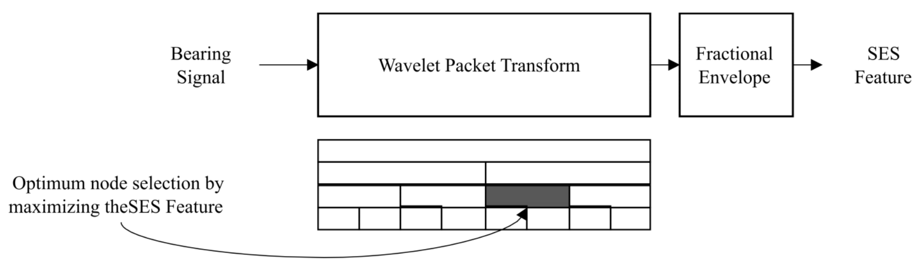


Figure 4.4: Proposed fault diagnosis using FrFT based fractional enveloping and wavelet packet transform

4.4 Results and Discussion

There are many important signal processing methods applied to bearing fault diagnosis, as discussed in the literature review. In this section, significant signal processing methods - fast kurtogram, wavelet transform, autogram, empirical mode decomposition and variational mode decomposition - are studied, implemented and compared with the fractional enveloping using three representative examples.

4.4.1 Case 1: Inner Race fault (CWRU-2013)

A case of inner race fault from CWRU 2013 dataset is considered as a representative case. In this case, the bearing under test is located at the drive end, whereas the accelerometer signal is measured using a secondary accelerometer located at the fan end. As per the benchmark [169], this case is a partially diagnosed case when conventional Hilbert transform based enveloping is used.

4.4.1.1 Fast Kurtogram

As discussed in Chapter 2, the research on processing of bearing fault signals revolves around finding the optimal resonance band to enhance the bearing signature in spectral domain. In order to select this optimal band, spectral kurtosis is an effective feature and the fast kurtogram method depends on calculating the spectral kurtosis for a finite number of frequency bands as shown in Fig. 4.5. A detailed background of spectral kurtosis is given in [180]. The idea is to first divide the bearing signal into several frequency bands using a filter bank and then calculating the kurtosis values of the filtered signals. The largest value would ideally represent the bearing signature free from noise.

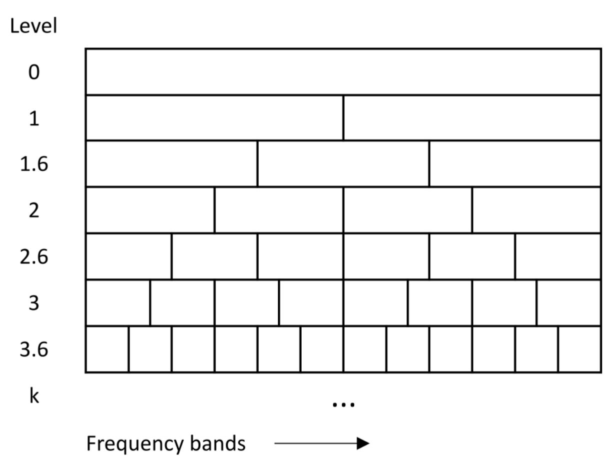
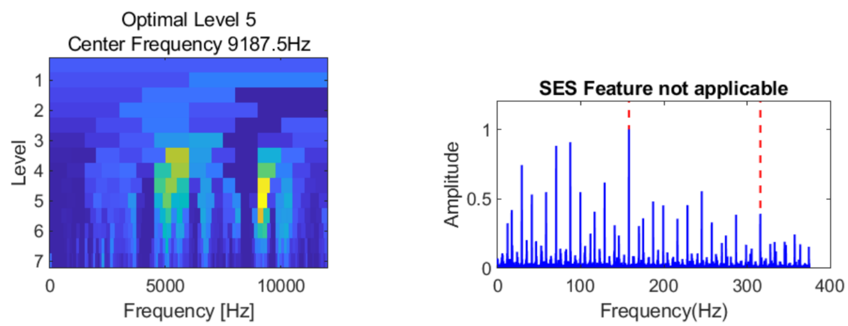


Figure 4.5: $\frac{1}{3}^{rd}$ tree structure of kurtogram method

Fig. 4.6 (a) shows the optimal band selection using the fast kurtogram and corresponding squared envelope spectrum of the filtered signal. The kurtogram method chooses the band centred at 9187.5 Hz with a bandwidth of 375 Hz corresponding to the maximum kurtosis. The envelope spectrum of the filtered signal, shown in Fig. 4.6 (b), has prominent inner race fault frequency.



(a) **(b)**

Figure 4.6: Case 1 : Analysis using fast kurtogram (a) Optimal node selection using maximum value of kurtosis, (b) Corresponding squared envelope spectrum

However, there are two important drawbacks of the kurtogram method. First, kurtosis based selection of optimal band may give erroneous results, especially if the signal has strong impulses from other components. Second, signal length of the filtered signals is not consistent for this method. From the implementation of view, this limits the use of this method and it can not be used for automatic fault diagnosis.

4.4.1.2 Wavelet Transform

Wavelet transform is a tool for muti-resolution analysis and can be interpreted as a filter bank. The dyadic decomposition using wavelets divides the frequency into discrete number of bands. If the spectral kurtosis is calculated for these bands, a modified kurtogram technique can be implemented with the advantages of the wavelet transform. Using maximal overlap wavelet packet transform, the signal can be decomposed with consistent signal length, as opposed to the fast kurtogram. For this study, Case 1 is analysed using wavelets from Daubechies (db) and Fejér-Korovkin (fk) families.

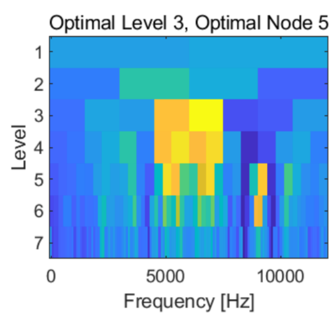
Although wavelet based method provides better spectral features, its performance largely depends on the selection of proper wavelet basis. This issue is widely discussed

Table 4.1: Effect of mother wavelet. Daubechies (db), Fejér-Korovkin (fk).

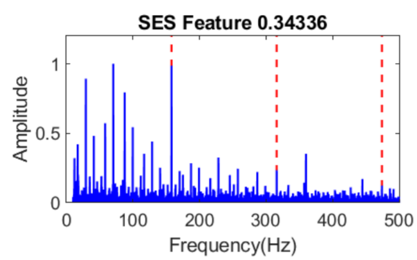
Mother Wavelet	Optimal Level	Optimal Node	SES Feature
db8	3	5	0.3433
db3	4	8	0.2631
fk14	3	5	0.3401
fk4	4	9	0.2978

in the literature. However, it is difficult to choose an appropriate wavelet from a large pool of available candidates. To demonstrate how this choice affects the end result, Case 1 results for different mother wavelets are given in Table. 4.1. It can be observed from the table that the SES feature values vary significantly. It is maximum for *db8*, whereas minimum for *db3*.

Fig. 4.7 shows the optimal node selection using *db8* wavelet. It chooses a broader band of 1500 Hz centred at 6750 Hz, when compared to the fast kurtogram method.



(a)

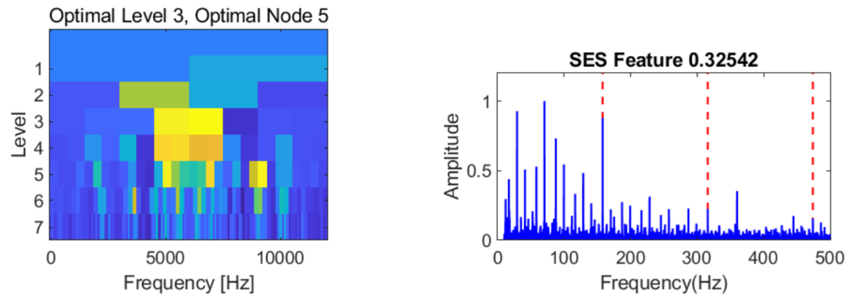


(b)

Figure 4.7: Case 1 : Analysis using wavelet transform (a) Optimal node selection using maximum value of kurtosis, (b) Corresponding squared envelope spectrum

4.4.1.3 Autogram

Due to the drawbacks of the kurtogram method, several modifications are suggested in the literature. Autogram is one such modification, in which, rather than finding the kurtosis of band-pass filtered signals, the kurtosis values of their autocorrelation are calculated. The results of this method are shown in Fig. 4.8.



(a) **(b)**

Figure 4.8: Case 1 : Analysis using Autogram (a) Optimal node selection using maximum value of kurtosis, (b) Corresponding squared envelope spectrum

Autogram chooses a completely different band centred around 6750 Hz with a bandwidth of 1500 Hz. The corresponding spectrum thus has slightly less prominent fault harmonics with SES feature equal to 0.3254, but the 1x peak (related to the rotational speed) is more prominent compared to the fast kurtogram method.

Both the drawbacks of the kurtogram method are well addressed using the autogram method. The use of kurtosis may still create problems in some cases, thus it is a common practice to use other sparsity indices, like gini index, L_2/L_1 norm, Hoyer index. The major issue with this method is that it is not readily applicable for fault diagnosis under variable speed conditions. It also takes 73% more time compared to the wavelet transform method.

4.4.1.4 Empirical Mode Decomposition (EMD)

Although, wavelets are advantageous over the conventional filter bank, it poses a serious question of selection of base wavelet for bearing fault analysis. This issue is demonstrated in Table 4.1. Empirical mode decomposition solves this problem by adaptively decomposing the signal into several intrinsic mode functions (IMF) having a slowly varying, non-decreasing instantaneous frequency concentrated around a central value. Optimal IMF is often chosen by calculating the correlation coefficient between the original signal and the IMF. For analysis purposes, the selection of optimal IMF is carried out by maximising the kurtosis, similar to the methods discussed above.

The results of this method are shown in Fig. 4.9. It takes very less amount of computational time (0.7 sec) and the performance is comparable to other methods in this case, that is the SES feature is equal to 0.3104.

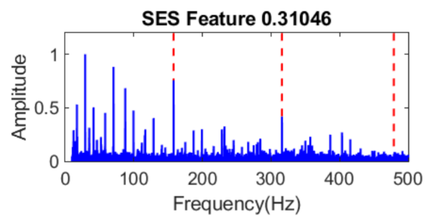


Figure 4.9: Case 1 : Analysis using Empirical Mode Decomposition

But, EMD faces a problem of mode-mixing, which is not apparent in these representative cases. The solution to mode-mixing is a topic of interest in the field and includes several modifications of EMD, like ensemble EMD (EEMD), complementary EEMD with adaptive noise (CEEMDAN) and variational mode decomposition.

4.4.1.5 Variational Mode Decomposition (VMD)

Variational mode decomposition involves minimising a constrained variational problem to find a set of IMFs and their central frequencies [181]. This method is computationally expensive compared to the empirical mode decomposition. The results of VMD are shown in Fig. 4.10. The SES feature value for Case 1 is 0.3485, which is highest compared to other methods. But, the time taken by the algorithm is larger due to the optimisation problem involved.

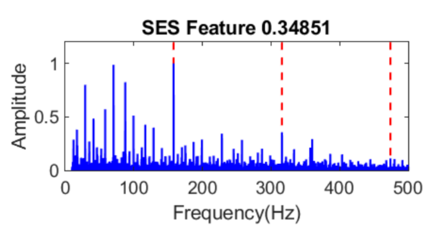


Figure 4.10: Case 1 : Analysis using Variational Mode Decomposition

4.4.1.6 Fractional Enveloping

As discussed earlier fractional enveloping provides a way to enhance the performance of existing methods. The results in Fig. 4.11 show the spectrum plots for fractional envelope alone and applied with other signal processing methods. It can be observed from the figures that the SES feature is significantly improved with the help of fractional enveloping. Also the performance of empirical mode decomposition followed by fractional enveloping (EMDFE) is comparatively better. The SES feature values for variational mode decomposition and fractional enveloping (VMDFE) and wavelet packet transform and fractional enveloping (WPTFE) are also comparable.

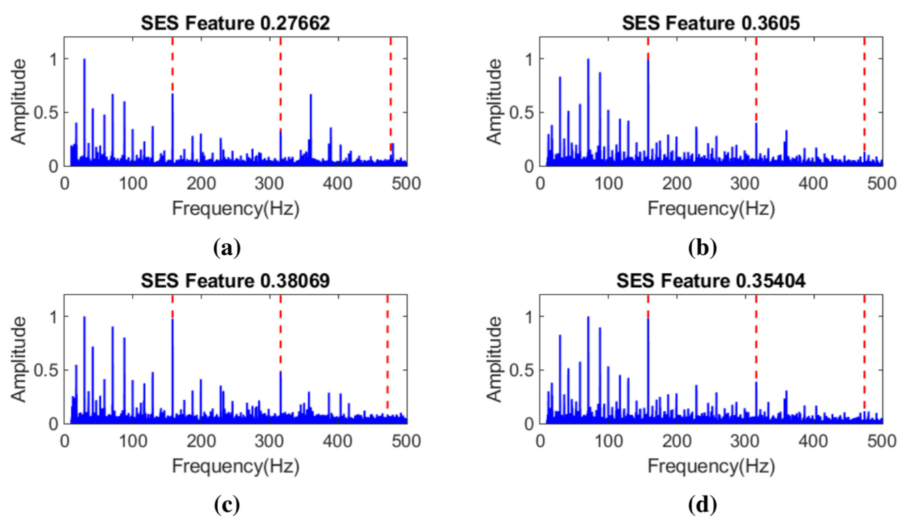


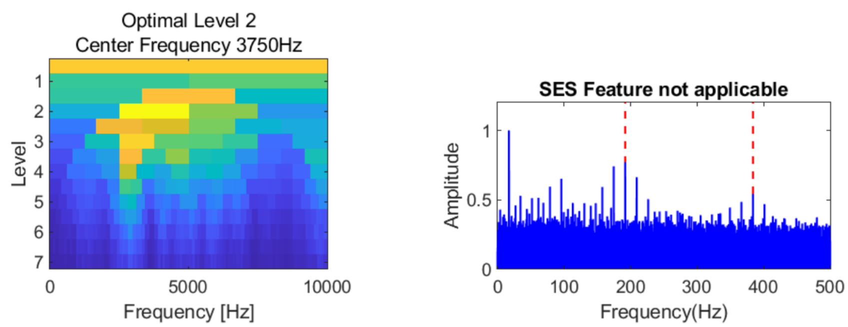
Figure 4.11: Case 1 : Analysis using fractional enveloping. Envelope spectrums using (a) only fractional envelope, (b) wavelet transform (db8) and fractional envelope, (c) empirical mode decomposition and fractional envelope, and (d) variational mode decomposition and fractional envelope

4.4.2 Case 2: Sound Signal (BITS-2021)

Second example is an inner race fault of 0.6 mm from the BITS-2021 dataset. The bearing is monitored using a microphone and the sound signal acquired from the faulty bearing is processed using the available methods.

4.4.2.1 Fast Kurtogram

The optimal band selection using the fast kurtogram and corresponding squared envelope spectrum of the filtered signal are shown in Fig. 4.12. The kurtogram method chooses the band centred at 3750 Hz with at level 2 corresponding to the maximum kurtosis. However, the noise floor is significantly larger. Sound signal is often corrupted by noise and the kurtogram method does not effectively reduce this noise, as observed in Fig. 4.12. It is also observed that, the peaks at the fault harmonics are still sufficiently large to infer this case as an inner race fault case.



(a) (b)

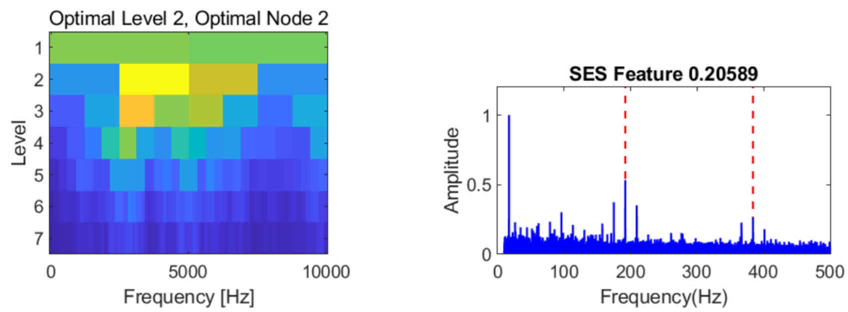
Figure 4.12: Case 2 : Analysis using fast kurtogram (a) Optimal node selection using maximum value of kurtosis, (b) Corresponding squared envelope spectrum

4.4.2.2 Wavelet Transform

The wavelet transform based method chooses optimal node 2 at level 2, as shown in Fig. 4.13. The noise floor is significantly reduced compared to the fast kurtogram method. The SES feature value is 0.2058. The computational time taken by this method is comparatively larger than kurtogram, but based on its performance, this method provides an efficient way of enhancing fault features.

4.4.2.3 Autogram

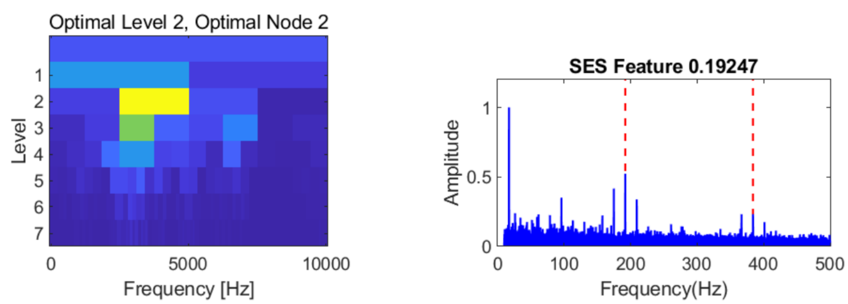
The results of Autogram method for Case 2 are shown in Fig. 4.14. Autogram also chooses a the optimal node 2 at level 2, but its SES feature value is 0.1924, significantly



(a) **(b)**

Figure 4.13: Case 2 : Analysis using wavelet transform (a) Optimal node selection using maximum value of kurtosis, (b) Corresponding squared envelope spectrum

less compared to the wavelet transform. This may be due to the autocorrelation step in the Autogram method.



(a) **(b)**

Figure 4.14: Case 2 : Analysis using Autogram (a) Optimal node selection using maximum value of kurtosis, (b) Corresponding squared envelope spectrum

4.4.2.4 Empirical Mode Decomposition (EMD)

The results of this method are shown in Fig. 4.15. The corresponding SES feature is equal to 0.22.

4.4.2.5 Variational Mode Decomposition (VMD)

The results of VMD are shown in Fig. 4.16. The SES feature value for Case 2 is 0.18, which is poor compared to other methods.

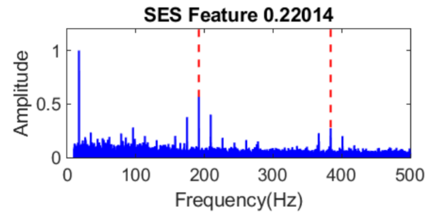


Figure 4.15: Case 2 : Analysis using Empirical Mode Decomposition

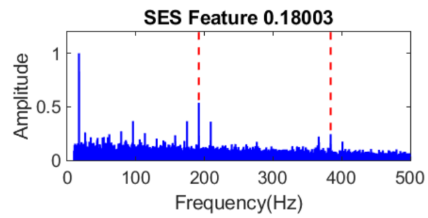


Figure 4.16: Case 2 : Analysis using Variational Mode Decomposition

4.4.2.6 Fractional Enveloping

The results in Fig. 4.17 show the spectrum plots using fractional enveloping methods. It can be observed from the figures that the SES feature is significantly improved with the help of fractional enveloping. Also the performance of wavelet packet transform followed by fractional enveloping (WPTFE) is comparatively better.

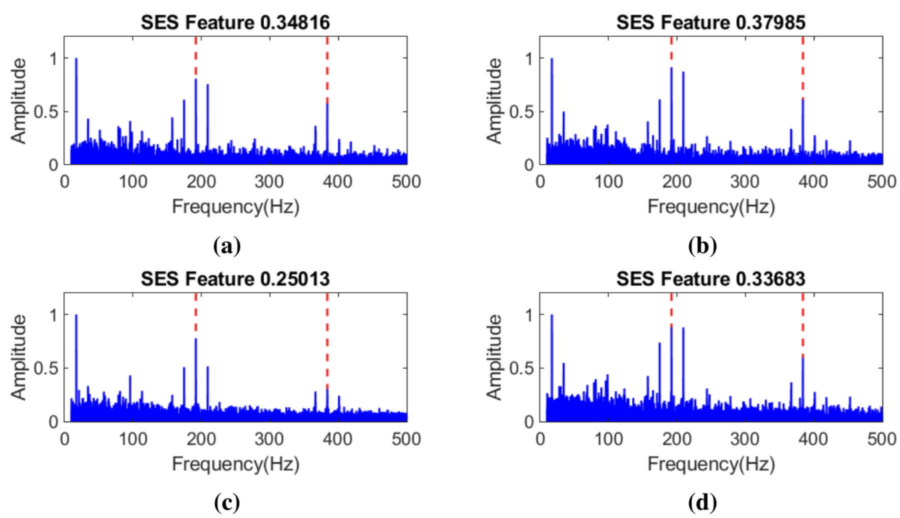


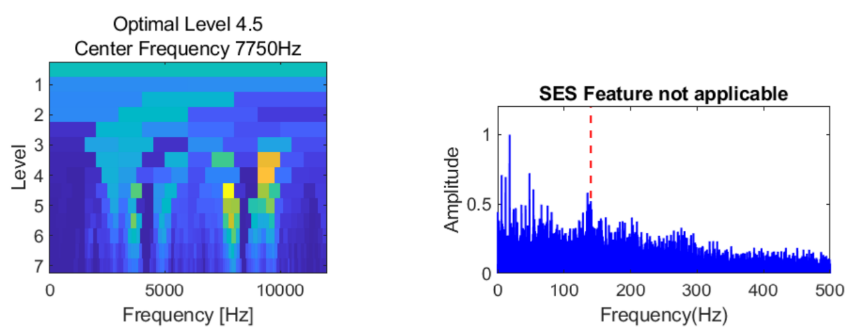
Figure 4.17: Case 2 : Analysis using fractional enveloping. Envelope spectrums using (a) only fractional envelope, (b) wavelet transform (db8) and fractional envelope, (c) empirical mode decomposition and fractional envelope, and (d) variational mode decomposition and fractional envelope

4.4.3 Case 3: Rolling Element Fault (CWRU-2013)

Third example is a rolling element fault of 14 mil from the CWRU-2013 dataset. The bearing is monitored using an accelerometer located on the housing of the bearing under test and the vibration signal acquired is processed using the available methods.

4.4.3.1 Fast Kurtogram

The optimal band selection using the fast kurtogram and corresponding squared envelope spectrum of the filtered signal are shown in Fig. 4.18. The kurtogram method chooses the band centred at 7750 Hz, level 4.5 corresponding to the maximum kurtosis. However, the noise floor is significantly larger. Rolling element fault is often suppressed by noise and the kurtogram method does not effectively reduce this noise, as observed in Fig. 4.18. It is also observed that, the peaks at the fault harmonics are smeared and it is difficult to infer this case as a rolling element race fault case.

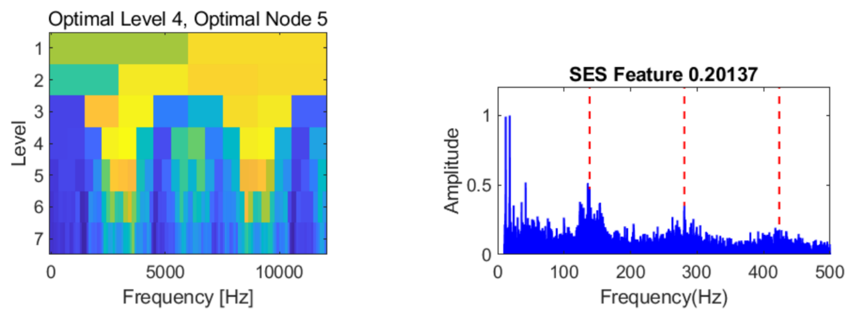


(a) **(b)**

Figure 4.18: Case 3 : Analysis using fast kurtogram (a) Optimal node selection using maximum value of kurtosis, (b) Corresponding squared envelope spectrum

4.4.3.2 Wavelet Transform

The wavelet transform based method chooses optimal node 5 at level 4. After simulations for *Daubechies (db)* and *Fejer-Korovkin (fk)*, fk4 is selected as a suitable wavelet for this case. As observed in Fig. 4.19, the noise floor is significantly reduced compared to the fast kurtogram method. The SES feature value is 0.2. Smearing of the fault peak is still observed in the spectrum.

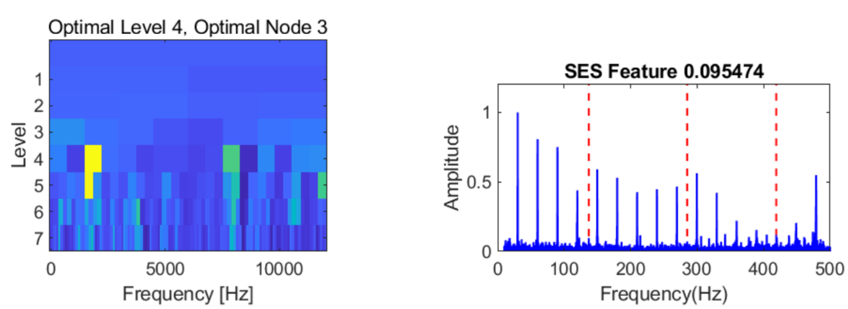


(a) (b)

Figure 4.19: Case 3 : Analysis using wavelet transform (fk4) (a) Optimal node selection using maximum value of kurtosis, (b) Corresponding squared envelope spectrum

4.4.3.3 Autogram

The results of Autogram method for Case 3 are shown in Fig. 4.20. Autogram also chooses the optimal level 4, but its SES feature value is 0.09, significantly less compared to the wavelet transform. The fault peaks, however, are completely suppressed in the spectrum and the speed harmonics are dominant.



(a) (b)

Figure 4.20: Case 3 : Analysis using Autogram (a) Optimal node selection using maximum value of kurtosis, (b) Corresponding squared envelope spectrum

4.4.3.4 Empirical Mode Decomposition (EMD)

The results of this method are shown in Fig. 4.21. The corresponding SES feature is equal to 0.21. Smearing of the fault peaks is observed in the spectrum.

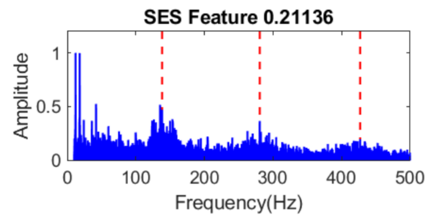


Figure 4.21: Case 3 : Analysis using Empirical Mode Decomposition

4.4.3.5 Variational Mode Decomposition (VMD)

The results of VMD are shown in Fig. 4.22. The SES feature value for Case 2 is 0.09, which is poor compared to other methods.

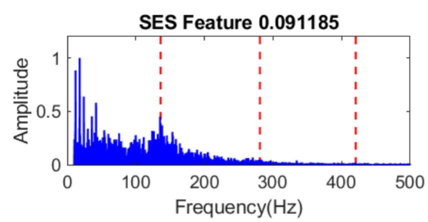


Figure 4.22: Case 3 : Analysis using Variational Mode Decomposition

4.4.3.6 Fractional Enveloping

The results in Fig. 4.23 show the spectrum plots using fractional enveloping methods. It can be observed from the figures that the SES feature is significantly improved with the help of fractional enveloping. The performance of wavelet packet transform followed by fractional enveloping (WPTFE) is comparatively better, with the SES feature value of 0.41 because of the sharper and prominent fault peaks.

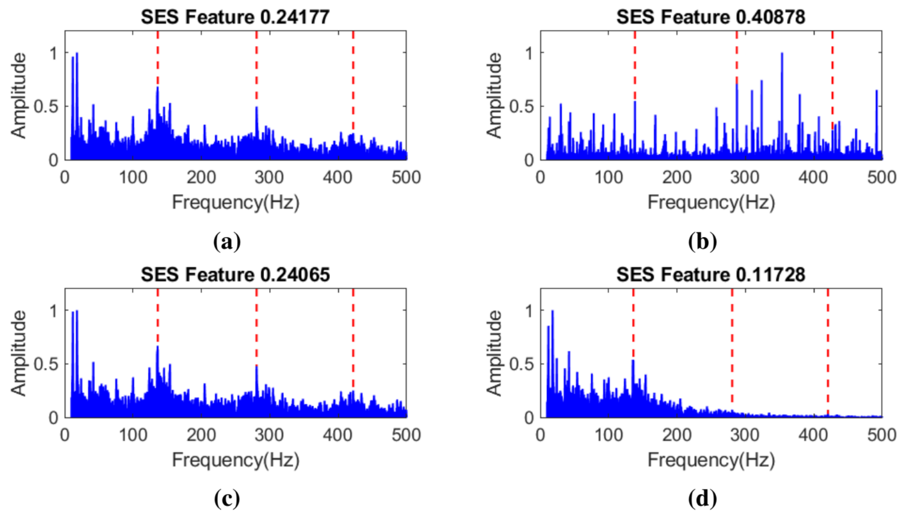


Figure 4.23: Case 3 : Analysis using fractional enveloping. Envelope spectrums using (a) only fractional envelope, (b) wavelet transform (fk4) and fractional envelope, (c) empirical mode decomposition and fractional envelope, and (d) variational mode decomposition and fractional envelope

4.5 Conclusion

Signal enveloping is an irreplaceable part of signal processing for bearing faults. Fractional enveloping is a generalisation of the convention Hilbert transform based enveloping and it provides a way to enhance the performance of existing signal processing algorithms. Out of the available methods of calculating the fractional envelope of a signal, the fractional Fourier transform method is found to be most suitable for bearing fault diagnosis. Its utility is proved by enhancing the kurtosis values in the fractional domain. As kurtosis alone is not enough for diagnosing the faults, a frequency domain feature, named SES feature, is also investigated using the representative cases from CWRU-2013 and BITS-2021 datasets. It is observed that the wavelet packet transform followed by fractional enveloping enhances the SES feature significantly. The drawback of this method is the increased computation. If fractional enveloping is used with wavelet transform, the inherent drawbacks of wavelets also become significant. To further improve the performance, another method is proposed in next chapter.