Chapter 4

Micro-Doppler Signatures for Target Identification

When the transmitted signal of a coherent radar system hits moving targets, the carrier frequency of the signal will be shifted and is known as the Doppler effect. The Doppler frequency shift reflects the velocity of the moving target. Mechanical vibration or rotation of a target, or structures on the target, may induce additional frequency modulations on the returned radar signal, which generate sidebands about the target’s Doppler frequency, called the micro-Doppler effect [17]. Micro-Doppler radar signatures can provide unique information for recognition of targets of interest, for example, it has been used to identify the natural resonant frequency of a tractor trailer truck [65]. The m-D features of Jet Engine Modulation (JEM) lines in a Mi-24 Hind-D helicopter have also been used to estimate the turbine rotation rate and the number of turbine blades [66].

In this chapter, we demonstrate examples of micro-Doppler signatures of a target that can be used as radar signatures for target identification. Experimental trials were conducted to investigate and resolve the micro-Doppler radar signatures of a target using an X-band radar. Joint time-frequency analysis is the basis of most of the existing methods used to extract m-D features [17]. In section 4.1, we demonstrate the application of adaptive chirplet analysis for the separation of main body signal and rotating part. In section 4.2, the effectiveness of Fourier Bessel transform in conjunction with Fractional Fourier transform, is shown for extracting micro-Doppler features from the rotating targets.
4.1 Adaptive Chirplet Analysis

Recent studies show that radar signal can be properly modeled using the chirplet basis function [70]. Many events, especially those found in nature, can be modeled as the superposition of short-lived chirp functions. The chirplet transform has been recently used in areas such as multi-component signal detection, instantaneous frequency estimation, time-varying filter design, and interference excision [68–70]. In this work, the adaptive Gaussian chirplet decomposition is employed to extract m-D features.

The Gaussian chirplet is defined as [68]:

$$h_k(t) = \sqrt{\frac{\alpha_k}{\pi}} \{ \exp{\left( -\frac{\alpha_k}{2} (t - t_k)^2 \right)} + j(\omega_k(t - t_k) + \frac{\beta_k}{2} (t - t_k)^2) \}$$  \hspace{1cm} (4.1)

where $\alpha_k > 0$, $t_k, \omega_k, \beta_k \in \mathbb{R}$ $(t_k, \omega_k)$ indicates the time and frequency center of the linear chirp function, the variance $\alpha_k$ controls the width of the chirp function, and the parameter $\beta_k$ determines the rate of change of frequency. When the chirp rate $\beta_k$ is equal to zero and the parameter $\alpha_k$ approaches zero, the linear chirplet function $h_k(t)$ reduces to a sinusoidal signal. The adaptive spectrogram for the Gaussian chirplet is given as [69,70],

$$AS(t, \omega) = 2 \sum_k |B_k|^2 \exp\{ -\frac{\alpha_k}{2} (t - t_k)^2 - \frac{1}{\alpha_k} (\omega - \omega_k - \beta_k t)^2 \}$$  \hspace{1cm} (4.2)

where $B_k$ is the adaptive coefficient. The algorithm used here estimates the optimal elementary functions in the adaptive signal decomposition. Converting the optimization process to a traditional curve-fitting problem is the basic idea behind this algorithm. A more detailed description of the algorithm is given in [69,70]. The radar returns from the target body and the rotating part can be more easily separated based on the parameters of the chirplet bases, particularly $\alpha_k$ and $\beta_k$. This is because signals from the main body and the rotating part are captured by chirplet bases with different parameters.

We separate the body signal from the rotating part using threshold values of $\alpha_k$ and $\beta_k$. After the separation, we process the main body signal and the rotating part signal individually for better information extraction. This includes both the extraction of the geometrical features from the main body and the m-D features from the moving parts. Following the extraction of m-D features from the radar returned signal using chirplet analysis, the time-frequency signatures of the m-D features can be utilized to visualize the oscillation and to extract motion parameters related to the target of interest.
4.1 Adaptive Chirplet Analysis

4.1.1 Results

4.1.1.1 Stationary and rotating corner reflectors

High-range resolution (HRR) profiles were collected using a stepped frequency waveform (SFWF) radar mode at X-band between 9.0 to 9.4 GHz, i.e., a synthetic bandwidth of 400 MHz; the frequency step size was 1 MHz. The test target was made up of four corner reflectors, three of which are stationary to provide a geometric reference and a contrast to the shape of the oscillating reflector in the HRR profiles. The test target was located at 2 km from the radar system. HRR scans were performed at 2 kHz PRF. This data set is used to extract the m-D features using adaptive chirplet-based method incorporated with time-frequency analysis. Figure 4.1a illustrates the time-frequency signature of the original signal. The adaptive chirplet-based analysis is now used to separate the stationary and oscillating components. After the separation, time-frequency distribution series is used to obtain the time-frequency signature of the stationary and oscillating parts. Figures 4.1b and 4.1c illustrate the time-frequency signature of the extracted body signal and oscillation signal, respectively. Results demonstrate that the adaptive chirplet-based method is an effective tool to extract m-D features.

4.1.1.2 Experimental helicopter data

Experimental trials were conducted to investigate and resolve the micro-Doppler radar signatures of a target using an X-band radar. The target in this experiment is a hovering helicopter [15]. Joint time-frequency analysis is the basis of most of the existing methods used to extract m-D features. In this work, we used adaptive chirplet decomposition along with the time-frequency distribution series for the extraction of m-D features. The rotational motion of rotor blades in a helicopter imparts a periodic modulation on radar returns. The rotation-induced Doppler shifts relative to the Doppler shift of the fuselage (or body) occupy unique locations in the frequency domain. Whenever a blade has specular reflection such as at the advancing or receding point of rotation, the particular blade transmits a short flash to the radar return. The rotation rate of the rotor is directly related to the time interval between these flashes. The duration of a flash is determined by the radar wavelength and by the length and rotation rate of the blades [15].

To follow the procedure of m-D analysis, first, the Fourier transform of the original radar returned data is computed and the image obtained is shown in
Figure 4.1: a) Time-frequency signature of the original signal, b) Time-frequency signature of the extracted body signal, and c) Time-frequency signature of the extracted oscillating signal.
4.1 Adaptive Chirplet Analysis

Figure 4.2: Fourier transform of the original signal.

Figure 4.2. As can be seen from the image, a main frequency bin with a large amplitude exists in the middle of the spectrum representing the helicopter’s body vibration. Surrounding this frequency bin, one can observe two other less prominent peaks representing the frequency of the main rotor and tail rotor rotation rate. These are the m-D features that are to be extracted. By applying the adaptive chirplet analysis as described above, the m-D features are obtained. The next step in the procedure is to make use of time-frequency analysis in order to depict the m-D oscillations and to estimate the target’s motion parameters. The time-frequency signature of the original returned signal using time-frequency distribution series is given in Figure 4.3a. The stationary body is observed as a fairly constant signal at 0 Hz on the frequency axis. The micro-motion dynamics of the tail rotor are seen as small, quick flashes just below the constant stationary body. The micro-motions of the main rotor are not clearly visible as the three large flashes with the large period. The time-frequency signature of the extracted body signal and oscillating signal are given in Figures 4.3b and 4.3c. In Figure 4.3c, not only are the flashes made clearer, but the flashes are in fact stronger peaks than those observed in the time-frequency signature of the original signal in Figure 4.3a. The rotation rate of the main rotor blades is calculated from Figure 4.3c as follows. It is known that the main rotor of this helicopter has five blades. This is an important point as it means that the specular reflection at the advancing and receding point of rotation do not coincide with one another. Therefore, the resulting time-frequency plot will show alternating strong and weak flashes. This is indeed the case in Figure 4.3c. The period between the two strong flashes, i.e. the period between two blades at the advancing point
Figure 4.3: a) Time-frequency signature of the original signal; b) Time-frequency signature of the extracted body signal; and c) Time-frequency signature of the extracted oscillating signal.
of rotation, is 0.0591 s. Since there are five blades, this value is multiplied by five in order to obtain 0.2955 s, the length of time taken by a single blade to complete one full rotation. The number of rotations in one minute is given by \((60 \text{ s/min})/(0.2955 \text{ s/rotation}) = 203.05 \text{ rpm}\), which is in agreement with the actual value known to be 203 rpm. Similarly, the rotation rate of the tail rotor is measured using Figure 4.3c in a similar manner as it was computed for the main rotor. The rotation rate is calculated to be approximately 1031 rpm.

4.1.1.3 Conclusion

In this section, we presented a procedure for m-D analysis in order to extract the m-D features of radar returned signals from targets. The method combines both adaptive chirplet-based and time-frequency analysis in order to extract the m-D features of radar target returns. This methodology has been applied to stationary and rotating corner reflectors data and helicopter data. The results show that the proposed methodology is an effective tool for extracting m-D features. The rotation rates of the main rotor and tail rotor blades of the helicopter are successfully computed. In general, it is shown that the results are much improved after the m-D extraction has taken place. The experimental results agree with the expected outcome.

4.2 Fourier Bessel and Fractional Fourier Transform

In this section, we propose for the first time to use Fourier Bessel and Fractional Fourier Transform to extract micro-Doppler (m-D) features. To extract the m-D features from the radar signal returns, the time domain radar signal has to be decomposed into stationary and non-stationary components. This can be achieved by applying FBT and FrFT to the radar returns and choosing the Fourier-Bessel (FB) coefficients corresponding to the stationary and the non-stationary components. The stationary and the oscillating signals can be reconstructed by applying the inverse Fourier-Bessel transform (IFBT) on the selected FB coefficients. After the separation of the m-D features from the target’s original radar return, time-frequency analysis is then used to estimate the motion parameters of the target.
4.2 Fourier Bessel and Fractional Fourier Transform

4.2.1 Fourier-Bessel Transform

The FBT decomposes a signal into a weighted sum of an infinite number of Bessel functions of zeroth-order. Mathematically, the FBT $F(\rho)$ of a function $f(r)$ is represented as [51]:

\[
F(\rho) = 2\pi \int_0^\infty f(r) J_0(2\pi \rho r) r dr
\] (4.3)

\[
f(r) = 2\pi \int_0^\infty F(\rho) J_0(2\pi \rho r) \rho d\rho
\] (4.4)

where $J_0(2\pi \rho r)$ are the zeroth-order Bessel functions and $\rho$ is transform variable.

FBT is also known as Hankel transform. As the FT over an infinite interval is related to the Fourier series over a finite interval, so the FBT over an infinite interval is related to the FB series over a finite interval. FB series expansion of a signal $x(t)$, in the interval $(0, T)$ is given as [45]:

\[
x(t) = \sum_{r=1}^{M} A_r J_0(\frac{\alpha_r}{T} t), 0 < t < T
\] (4.5)

FB coefficients, $A_r$ are computed by using following equation.

\[
A_r = \frac{2 \int_0^T t x(t) J_0(\frac{\alpha_r}{T} t) dt}{T^2 [J_1(\alpha_r)]^2}
\] (4.6)

where $\alpha_r$, $r = 1, 2, 3, ..., M$ are the ascending order positive roots of $J_0(t) = 0$. Since Bessel function supports a finite bandwidth around a center frequency, the spectrum of the signal can be represented better using FB expansion. As the Bessel functions form orthogonal basis and decay over the time, non-stationary signals can be better represented using FB expansion [52]. It turns out to be a one-to-one relation between frequency content of the signal and the order of the FB expansion, where the coefficients attain maximum amplitude [53]. As the center frequency of the signal is increased, it is observed that the order of the FB Coefficients is increased. Similarly there is a relationship between the bandwidth of the signal and the range of FB Coefficients. In particular, the range of FB Coefficients increases with the increase in the bandwidth of the signal [54]. Since both amplitude modulation (AM) and frequency modulation (FM) are part of the Bessels’s basis function, the FB expansion can represent the reflected signal from a rotating target more efficiently.
4.2.2 Fractional Fourier Transform

Fractional Fourier transform (FrFT) is the generalization of the classical Fourier transform. The applications of FrFT can be found in signal processing, communications, signal restoration, noise removal and in many other science disciplines. It is a powerful tool used for the analysis of time-varying signals. The FrFT is a linear operator that corresponds to the rotation of the signal through an angle i.e. the representation of the signal along the axis $u$, making an angle $a$ with the time axis. The $a$ th order Fractional Fourier Transform of the function $f(u)$ is defined as [58]:

$$f_a(u) = \int f(u')K_a(u, u')du', \quad (4.7)$$

$$K_a(u, u') = A_\phi e^{i\pi (\cot \phi u^2 - 2 \csc \phi uu' + \cot \phi u^2)} \quad (4.8)$$

where

$$\phi = \frac{a\pi}{2} \quad (4.9)$$

$$A_\phi = \sqrt{1 - i \cot \phi} \quad (4.10)$$

For $a = 1$, we find that $\phi = \frac{\pi}{2}$, $A_\phi = 1$ and

$$f_1(u) = \int_{-\infty}^{\infty} \exp(-i2\phi uu')f(u')du' \quad (4.11)$$

for $a = 0$, FrFT reduces into identity operation. For $a = 1$, FrFT is equal to standard FT of $f(u)$. For $a = -1$, FrFT becomes an inverse FT. FrFT can transform a signal either in time or in frequency domain into a domain between time and frequency. FrFT depends on the parameter $a$ and can be interpreted as rotation by an angle $a$ in the time-frequency plane. The FrFT of a signal can also be interpreted as a decomposition of the signal in terms of chirps [59].

4.3 Simulation Results

In this section, we demonstrate the application of the proposed method by removing the cross terms in the WVD representation of a multi-component signal. Consider a discrete time domain signal, $s[n]$, which is sum of the three linear chirps given by:

$$s[n] = \sum_{i=1}^{3} A_i \exp(2\pi f_i nT + \frac{1}{2} \beta_i (nT)^2) \quad (4.12)$$
where $A_i$ are the amplitudes of the constituent signals, $f_i$ are the fundamental frequencies, $\beta_i$ are chirp rates and $T$ is the sampling interval. Figure 4.4a and Figure 4.4b show the STFT and WVD representations of the multi component signal in the equation 4.12. From Figure 4.4a, it is evident that STFT representation of the signal is free from cross terms but its time and frequency resolutions are poor. As expected, WVD gives good time and frequency resolution but is corrupted with the occurrence of cross terms. In order to remove these cross terms, the signal is analyzed using FBT. FB coefficients are calculated using equation (4.6). Figure 4.5 shows the FB coefficients of the multi component signal. By taking the most significant order of the FB coefficients, the multi component signal can be decomposed into its individual components. Table 4.1 shows the order of the significant FB coefficients that are selected for each chirp signal. Individual components are reconstructed by applying IFBT using the selected FB coefficients. Figures 4.6a, 4.6b and 4.6c show the WVD representation of each component of the multi-component signal. Figure 4.6d shows the plot obtained by adding WVD representations of the three linearly frequency modulated (LFM) signals together.
4.3 Simulation Results

Figure 4.5: FB Coefficients of the multi component signal.

<table>
<thead>
<tr>
<th>signal</th>
<th>Required FB Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>chirp 1</td>
<td>(1-45)</td>
</tr>
<tr>
<td>chirp 2</td>
<td>(108-150)</td>
</tr>
<tr>
<td>chirp 3</td>
<td>(151-230)</td>
</tr>
</tbody>
</table>

Table 4.1: Required FB coefficients for each chirp.

Figure 4.6: (a−c) are WVD of first, second and third LFM chirp, respectively. d) FB-WVD plot of multi component signal.
4.3 Simulation Results

Figure 4.7: a) STFT of the LFM signal, b) STFT of LFM signal after rotation, c) STFT of separated first component, d) STFT of separated second component, e) STFT of separated first component after rotation, and f) STFT of separated second component after rotation.
Results in the Figure 4.6 show that the occurrence of cross terms in WVD can be eliminated, if the multi component signal is decomposed into its individual components, by expanding the signal using FB series and applying WVD to the constituent signals separately. Using FBT, we can separate the components of the multi-component signals, if their frequencies do not overlap in the frequency domain. But if their frequencies overlap in time and/or frequency domain, it is not possible to separate them using FBT. By using FrFT and FBT, we can separate the components of the multi-component signal whose frequencies overlap in time and/or frequency domain.

Figure 4.7a shows the STFT representation of the two LFM signals whose frequencies overlap in the frequency domain. Time-frequency characteristics of the signal was rotated by 36° in the clockwise direction by using FrFT, such that their frequency components do not overlap in the frequency domain. Figure 4.7b shows the STFT representation of the signal after rotation. Now using the FBT, the two frequency components of the multi-component signal were separated. Figure 4.7c and 4.7d show the separated components of the signal. After the separation of the components, time-frequency characteristics of the signal was rotated by 36° in the counterclockwise direction using FrFT. Figure 4.7e and Figure 4.7f show the separated LFM components. It should be emphasized here that this approach works well for any number of chirps with different angles.

4.4 Experimental Results

In this section, we demonstrate the application and effectiveness of the FB-TF method, with five different types of radar data obtained in various scenarios.

4.4.1 Rotating corner reflectors

Experimental trials were conducted to investigate and determine the m-D radar signatures of targets using an X-band radar. The target used for this experimental trial was a spinning blade with corner reflectors attached. These corner reflectors were designed in such a way that they reflect electromagnetic radiation with a minimal loss. These controlled experiments can simulate the rotating type of objects, generally found in an indoor environment such as a rotating fan and in an outdoor environment such as a rotating antenna or rotors. Controlled experiments allow us to set the desired rotation rate of the
target, to cross check and assess the results. A picture of the target is shown in Figure 4.8. This experiment was conducted with radar operating at 9.2 GHz and the pulse repetition frequency (PRF) was 1 kHz. The target employed in this experiment was at a range of 300 m from the radar and the distance between two reflectors is 38 inches. The corner length of the reflector is 10 inches and side length is 12 inches. STFT representation is utilized in order to depict the m-D oscillation. Figure 4.9a shows the STFT representation of the signal obtained from one rotating corner reflector, facing the radar. From the time-frequency signature, we can observe that the m-D of the rotating corner reflector is a time-varying frequency spectrum. Figure 4.9a clearly shows the sinusoidal motion of the corner reflector. The second weaker oscillation represents the reflection from the counter weight that was used to stabilize the corner reflector during the operation. It also contains a constant frequency component which is due to reflection from stationary body of the corner reflector. FBT was utilized in order to separate stationary component from the rotating component. Figure 4.9b shows the time-frequency signature of the extracted oscillating signal. Figure 4.9c shows the time-frequency signature of the extracted body signal. The rotation rate of the corner reflector is directly related to the time interval of the oscillations. From the additional time information, the rotation rate of the corner reflector is estimated at about 60 rpm. Similar analysis was done for the signals collected from two and three corner reflectors. Figure 4.10a shows the STFT representation of the original signal from two corner reflectors where as Figure 4.10b and Figure 4.10c show the time-frequency representations of the extracted oscillating signal and the extracted body signal, respectively. In this case, the rotation rate of the corner reflector was 40 rpm. Figure 4.11a shows the STFT representation of the signal when the target is rotating with three corner reflectors. Figure 4.11b
4.4 Experimental Results

Figure 4.9: a) TF signature of the signal from one rotating corner reflector facing the radar, b) TF signature of the extracted oscillating signal, and c) TF signature of the extracted body signal.
Figure 4.10: a) TF signature of the signal from two rotating corner reflector facing the radar, b) TF signature of the extracted oscillating signal, and c) TF signature of the extracted body signal.
4.4 Experimental Results

Figure 4.11: a) TF signature of the signal from three rotating corner reflector facing the radar, b) TF signature of the extracted oscillating signal, and c) TF signature of the extracted body signal.
4.4 Experimental Results

Figure 4.12: Top- the original SAR image at range cell; bottom- zoomed in SAR image.

and Figure 4.11c show the time-frequency representations of the extracted oscillating signal and extracted body signal, respectively. The estimated rotation rate of the corner reflector was about 60 rpm. Rotation rates estimated by the time-frequency analysis agree with the actual values.

### 4.4.2 Rotating antenna in SAR

Radar returns were collected from rotating antenna using APY-6 radar in SAR scenario. Using these data sets, we extracted the m-D features relating to a rotating antenna. The m-D features for such rotating targets may be seen as a sinusoidal phase modulation of the SAR azimuth phase history. The phase modulation may equivalently be seen as a time-varying Doppler frequency [21].

Figure 4.12 (top) shows the original SAR image and Figure 4.12 (bottom) shows the zoomed in SAR image between the range cells 115 and 130. The
4.4 Experimental Results

Figure 4.13: The Fourier Transform of the original time series.

Figure 4.14: a) TF signature of the original signal. b) TF signature of the extracted oscillating signal. c) TF signature of the extracted body signal.
Doppler smearing due to the rotating parts is often well localized in a finite number of range cells [21]. It is reasonable to process the Doppler signal for each range cell independently. Since the prior information about the location of the target is known, the data at the range cell 123 was analyzed using the FB-TF method. The Fourier transform of the original time series at range cell 123 is shown in Figure 4.13. The rotating antenna is located close to the zero Doppler and cannot be detected using FT method. Original time series was decomposed using FBT and rotating and stationary components of the signal were captured by different order of FB coefficients. Stationary signal and oscillating signals were reconstructed by applying IFBT on the selected coefficients.

Figure 4.14a illustrates the time-frequency signature of the original signal and Figure 4.14b illustrates the time-frequency signature of the extracted oscillating signal where as Figure 4.14c illustrates the time-frequency signature of the extracted body signal. Using the time-frequency plot, the rotation rate of the antenna is estimated by measuring the time interval between the peaks. The period is the time interval between peaks [21]. As an example, in Figure 4.14b, there are 3 peaks. The time interval between peak 1 and 2, between 2 and 3, and between 1 and 3 were measured. The average value was then used to estimate the rotation rate. The estimated rotation rate is 4.8 seconds, which is very close to the actual value of 4.7 seconds.

### 4.4.3 Manoeuvring air target in sea-clutter

The signals used in the following analysis were collected from the experimental air craft (King- Air 200). It was performing manoeuvres and being tracked by a high frequency surface wave radar (HFSWR) with a 10 - element linear receiving antenna array. HFSWR was operating at 5.672 MHz and scans were performed at a pulse repetition frequency of 9.17762 Hz. Each trial corresponds to a block of 256 pulses. Therefore, the CIT (coherent integration time) of each signal was 27.89 sec. As shown in Figure 4.15, the King-Air performed two figure-of-eight manoeuvres. Each figure-of-eight manoeuvre consisted of two circles with an approximate diameter of 10 km. The first figure-of-eight manoeuvre was performed at 200 ft (61m), while the second figure-of-eight manoeuvre was performed at 500 ft (152m). As shown in Figure 4.15, the location of the King-Air was marked by a square when each signal was collected. Each signal reflects a different scenario that could arise when tracking a manoeuvring aircraft. Since the sea clutter is more stronger...
Figure 4.15: Path of the King-Air 200 as a function of range (in km) and azimuth (in degrees).

than the target signal, detecting a target in the presence of the sea clutter is a challenging problem. For efficient detection and extraction of the target features, target signal has to be separated from the sea clutter and should be analyzed using time-frequency analysis. One way to separate the target signal from the sea clutter is to use digital filtering techniques in Frequency domain.

4.4.3.1 Filtering in Frequency domain

The Fourier spectra of the three signals are shown in Figures 4.16a, 4.16b and 4.16c, respectively. We observe that the target signal is buried in background that consists of clutter and noise (thermal and atmospheric). Here the sea clutter is due to Bragg scattering from the surface of the ocean [62]. The Fourier spectra contained two large spectral lines around the zero Doppler and sea clutter components were concentrated around zero Doppler. Figure 4.16c clearly illustrates that when the target is accelerating close to zero frequency or sea clutter, FT method fails to provide optimum detection performance [50].

Since the sea clutter appeared around zero Doppler, it can be removed using digital filtering techniques in frequency domain. Figure 4.17 shows the band-rejection filter that was used to filter the sea clutter. Figure 4.18a shows the STFT plot of the signal 1. By using band-rejection filter, sea clutter is removed. Figure 4.18b and 4.18c show the separated sea clutter and target
4.4 Experimental Results

Figure 4.16: a) FT of the signal 1, b) FT of the signal 2, and c) FT of the signal 3.
4.4 Experimental Results

Figure 4.17: Band-rejection filter.

Figure 4.18: a) STFT of signal 1, b) STFT of separated sea clutter of signal 1, and c) STFT of signal 1 after sea clutter is removed.

Above results show that target signal and sea clutter can be separated using filtering techniques in frequency domain. But these filtering techniques fail to separate the target signal from the sea clutter when the target signal crosses the sea clutter. Figures 4.19a and 4.20a show the STFT representation of the target signal crossing the sea clutter and Figures 4.19c and 4.20c show the STFT representation of the target signal, after the sea clutter is removed using band-rejection filter. Above results show that it is not possible to separate the target signal and sea clutter if the target is crossing the sea clutter. In the next section, we proposed a method to separate the target signal and sea clutter using Empirical Mode Decomposition.
4.4 Experimental Results

Figure 4.19: a) STFT of signal 2, b) STFT of separated sea clutter of signal 2, and c) STFT of signal 2 after sea clutter is removed.

Figure 4.20: a) STFT of signal 3, b) STFT of separated sea clutter of signal 3, and c) STFT of signal 3 after sea clutter is removed.
4.4 Experimental Results

Figure 4.21: a) EMD of the signal 1, b) EMD of the signal 2, and c) EMD of the signal 3.

Figure 4.22: a) STFT of the signal 1, b) STFT of the IMF 2 (sea clutter) of signal 1, and c) STFT of the IMF 1 (target) of signal 1.
4.4 Experimental Results

Figure 4.23: a) STFT of the signal 2, b) STFT of IMF 2 (sea clutter) of signal 2, and c) STFT of IMF 1 of signal 2 (target signal).

Figure 4.24: a) STFT of the signal 3, b) STFT of IMF 2 (sea clutter) of signal 3, and c) STFT of IMF 1 of signal 3 (target signal).
4.4 Experimental Results

4.4.3.2 Filtering using Empirical Mode Decomposition

In order to separate the target signal from the sea clutter, EMD (empirical mode decomposition) is performed on the radar returned signal and corresponding IMFs (intrinsic mode function) are extracted. Figure 4.21 shows the extracted IMFs form the signal 1, 2 and 3 respectively. Figure 4.22a shows the STFT of the signal 1. STFT of the extracted IMFs have been calculated and plotted in Figure 4.22b and 4.22c respectively. As the target signal and sea clutter are captured by different IMFs, EMD can be used to separate the target signal completely from the sea clutter. Signal 2 and signal 3 in Figures 4.23(a) and 4.24(a) correspond to the case where the target signal is crossing the sea clutter. EMD is applied on these signals and corresponding IMFs are extracted. Figures 4.23(c) and 4.24(c) show the STFT representation of the separated target signal from the signal 2 and signal 3, respectively. It can be seen that the sea clutter is completely removed from the signal but it also removed some portion of the target signal which is not desirable. Hence, EMD cannot be used to separate the target signal from the sea clutter if the target signal is crossing the sea clutter. In the next section, we proposed Fourier Bessel and Fractional Fourier transform based method to separate the target signal and sea clutter even when the target signal crosses the sea clutter.

4.4.3.3 Filtering using FB-TF method

Radar returns were analyzed using FBT and FB coefficients were calculated using equation 4.6. Figure 4.25 shows the plot of FB Coefficients of the signal 1. We can observe that radar returns from the sea clutter were captured by the lower order FB coefficients and the target signal was captured by the higher order FB coefficients of Fourier-Bessel basis functions. Since target signal and
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Figure 4.26: a) STFT of the signal 1, b) STFT of the (sea clutter) of signal 1, and c) STFT of the (target) signal 1 separated using FB-TF method.

Figure 4.27: a) STFT of the signal 2, b) STFT of IMF 2 (sea clutter) of signal 2, and c) STFT of IMF 1 of signal 2 (target signal).
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Figure 4.28: a) STFT of the signal 3, b) STFT of IMF 2 (sea clutter) of signal 3, and c) STFT of IMF 1 of signal 3 (target signal).

sea clutter are captured by different orders of FB coefficients, we can easily separate the target from the sea clutter.

Target signal was reconstructed by applying IFBT on the selected FB coefficients of the target. After the target signal is separated from the sea clutter, time-frequency representations like STFT was used to extract more information from it.

In the case of target signal crossing the sea clutter, as shown in Figures 4.27 (a) and 4.28(a), it is possible to separate them using FrFT and FBT. By using FrFT, the time-frequency signature of the signal is rotated in counter clockwise direction through an angle \( \theta \) such that the target signal is aligned perpendicular to the frequency axis around zero Doppler. Now the signal is analyzed using FBT and the target signal is separated by selecting the higher order FB coefficients corresponding to the target signal. The time-frequency signature of the target signal is reconstructed by applying IFBT on the selected FB coefficients. Now the time-frequency signature of the target signal is rotated in the clockwise direction through the same angle \( \theta \) to obtain the separated target signal. Figure 4.27(c) and Figure 4.28(c) show STFT representation of the signal 2 and 3 after the target signal is separated from
4.4 Experimental Results

Results in the Figure 4.27 and Figure 4.28 show the FB-TF method is an effective tool for separating the target signal from the strong sea clutter even when the target signal is crossing the sea clutter.

4.4.4 Quantitative Analysis

Clutter Attenuation (CA), Improvement Factor (IF) are used to compare the efficiency of EMD and FB-TF methods in suppressing sea clutter and enhancing the target signal. These two quantities are normally used to define the performance of Moving Target Indicator (MTI) systems. CA is defined as the ratio between the MTI filter input clutter power $C_i$ to output clutter power $C_o$ [63]

$$CA = \frac{C_i}{C_o}$$ \hspace{1cm} (4.13)

The IF is defined as ratio of Signal to Clutter Ratio (SCR) at the output to the SCR at the input [63],

$$IF = \left( \frac{S_o}{C_o} \right) / \left( \frac{S_i}{C_i} \right)$$ \hspace{1cm} (4.14)

which can be written as

$$IF = \frac{S_o}{S_i} CA$$ \hspace{1cm} (4.15)

where $S_i$ and $S_o$ are input target signal power and output target signal power. In order to calculate CA and IF values, power spectral density of the original signal is calculated and $C_i$, $S_i$ are measured. After applying FB-TF method to suppress the sea clutter, the power spectral density of the output signal is calculated and $C_o$, $S_o$ are measured. By substituting these values in the equations 4.13 and 4.14, CA and IF are calculated.

<table>
<thead>
<tr>
<th>Signal</th>
<th>Clutter Attenuation (CA) in dB</th>
<th>Improvement Factor (IF) in dB</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>53.26</td>
<td>53.07</td>
</tr>
<tr>
<td>2</td>
<td>51.12</td>
<td>50.86</td>
</tr>
<tr>
<td>3</td>
<td>50.45</td>
<td>50.17</td>
</tr>
</tbody>
</table>

Table 4.2: CA & IF values of frequency domain filtering method

From Tables 4.2, 4.3 and 4.4, we observe that CA and IF values of filtering in frequency domain method, EMD method and FB-TF methods are comparable in the case of signal 1. But in the cases of signal 2 and signal 3, CA and IF values are much higher for FB-TF method compared to EMD method and filtering in frequency domain method. This shows that, in the cases of
### 4.5 Conclusion

In this chapter, we presented a FB-TF based approach for m-D analysis, for the extraction of m-D features of the radar returned signals from the rotating targets, both in SAR and ISAR scenario. By applying the proposed method to simulated and several experimental data sets, the effectiveness of this FB-TF technique is confirmed. This method combines both FBT and time-frequency analysis to extract the m-D features of the radar returns. By applying the proposed method to the rotating antenna data and to the rotating corner reflectors data, the potential of the proposed method is ascertained. From the extracted m-D signatures, information about the target’s micro-motion dynamics such as rotation rate is obtained. The experimental results agree with the expected outcome. FB-TF proves to be a useful tool in the reduction of the sea clutter and target enhancement. Using FB-TF method, we could separate the target from the strong sea clutter. In the case of target signal crossing the sea clutter, target signal was separated from the sea clutter using the FrFT and FBT. The quantitative analysis distinctly demonstrates that FB-TF method significantly improves the signal-to-clutter ratio compare to the empirical mode decomposition method. Results demonstrate that proposed method could be used as potential tool for detecting and enhancing low observable maneuvering, accelerating air targets in the littoral environments.

<table>
<thead>
<tr>
<th>Signal</th>
<th>Clutter Attenuation (CA) in dB</th>
<th>Improvement Factor (IF) in dB</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>57.44</td>
<td>57.27</td>
</tr>
<tr>
<td>2</td>
<td>52.79</td>
<td>52.82</td>
</tr>
<tr>
<td>3</td>
<td>51.43</td>
<td>51.08</td>
</tr>
</tbody>
</table>

Table 4.3: CA & IF values of EMD method

<table>
<thead>
<tr>
<th>Signal</th>
<th>Clutter Attenuation (CA) in dB</th>
<th>Improvement Factor (IF) in dB</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>57.62</td>
<td>57.43</td>
</tr>
<tr>
<td>2</td>
<td>56.43</td>
<td>68.43</td>
</tr>
<tr>
<td>3</td>
<td>57.56</td>
<td>66.39</td>
</tr>
</tbody>
</table>

Table 4.4: CA & IF values of FB-TF method

target signal crossing the sea clutter, FB-TF gives better results compared to filtering in the frequency domain method and EMD method.
4.5 Conclusion