Chapter-5

'SVBSLET' WAVELET FOR LEAK DETECTION
5.1 INTRODUCTION

This chapter deals with the development of a new wavelet called ‘SVBSLET’. Though literature survey indicates methods for leakage detection using wavelet transformation, they are not directly suitable for signature identification of hydraulic oil leakage from rocket motor hardware. Hence, further work is carried out for development of a new wavelet. The need and design criteria for development of a new wavelet is explained. The wavelet function and scaling function of the new wavelet are detailed. Methodology adopted for processing the acoustic emission data corresponding to hydraulic oil leak is presented along with the results.

5.2 PROBLEM DEFINITION

As described in the previous chapter, the research work is focused mainly for signature identification of all the events viz., hydraulic noise, rubbing of fasteners and crack during the proof pressure testing of the rocket motors hardware. The developed method is able to successfully identify these events and there were no false abort conditions during the tests.

But, during some of the tests, leakage of hydraulic oil was observed from the rocket motor segment joint, which could not be identified by using the methods developed with the existing wavelets. Hence, an attempt is made to further develop a new wavelet to meet the requirements of this hydraulic oil leakage detection from rocket motor hardware.
5.3 THE NEW 'SVBSLET' WAVELET

The AE signal is denoised using Discrete Wavelet Transform (DWT) technique and the signal is reconstructed back. To denoise the signal, the detail coefficients are thresholded and are made zero. The signal is reconstructed back. For Denoising of a signal, choice of proper wavelet scaling function plays an important role. For effective denoising, any wavelet scaling function shall have properties similar to the original signal. Many wavelets available today have their own applications and each wavelet has its own characteristics. Because there are different types of wavelets, one of the major problems is to determine the best type of wavelet to use for a particular application.

With the available wavelets it may not be possible to carry out the analysis of all types of signals. Although Daubechies wavelet has been considered as the best wavelet for decomposition and reconstruction purposes, it is not matching with some of the signatures. In such situations it is necessary to design new wavelets to meet specific requirements [20].

The design criteria for a new wavelet are

i. All wavelet systems are generated from simple scaling and wavelet functions.

ii. All useful wavelet systems must satisfy the multi-resolution conditions.

iii. Filter Bank is necessary for the calculation of expansion coefficients.

Based on the above characteristics a new wavelet is developed and it is named as 'SVBSLET' wavelet. This wavelet
has its own scaling function $\phi(x)$ and wavelet function $\psi(x)$. This wavelet belongs to the family of orthogonal wavelet system. The scaling function and wavelet function of 'SVBSLET' wavelet are detailed below.

**The Scaling Function**

The wavelet function is defined in terms of scaling function. If $\phi(x)$ is a scaling function, then $\phi(2x)$ is the same function compressed by a factor of 2. The binary function can therefore be denoted as

$$\phi_j = \phi(2^j x) \quad \ldots \quad (5.1)$$

Like wise $\phi(2x-1)$ is a compressed function translated by 1. Multiple translation and compression of the scaling function can therefore be denoted as

$$\phi_{jk}(x) = \phi(2^j x - k) \quad \ldots \quad (5.2)$$

where $2^j$ is the scaling of $x$, $j$ is $\log_2$ of the scale and $k$ is an integer. From the above scaling function the wavelet function can be constructed, for $M$ coefficients as

$$\psi(x) = \sum (-1)^k C_{M,k} \phi(2x-k) \quad \ldots \quad (5.3)$$

**'SVBSLET' Wavelet function**

Based on the above theory and considering the Meyer wavelet as the mother wavelet, cosine function is chosen for construction of 'SVBSLET' wavelet function. Cosine function is chosen as the wavelet because the AE signal corresponding pure hydraulic oil leakage has a close correlation. Based on this the wavelet function is expressed as follows:
\[
\psi(x) = C \cos(x); \quad 0 < x < 2\pi
\]

\[
= 0 \quad ; \text{otherwise} \quad \ldots \ldots (5.4)
\]

where \( C \) is the constant that is used for normalization in view of reconstruction and to provide the better recovery of signals. Eqn.5.4 is considered as a wavelet because it satisfies the two important conditions:

i. The wavelet in the interval \([-\infty, \infty]\) must be always equal to zero, i.e., the average value of the wavelet in the time domain must be zero,

\[
\psi(x)dt = 0 \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (5.5)
\]

ii. The square integrable functions \( \psi(x) \) satisfying the admissibility condition can be used to first analyze and then reconstruct a signal without loss of information.

\[
\int \frac{\Psi(\omega)}{|\omega|} \, d\omega < +\infty \quad \ldots \ldots (5.6)
\]

In eqn.5.6, \( \Psi(\omega) \) is the Fourier Transform of \( \psi(t) \). The admissibility condition implies that the Fourier Transform of \( \psi(x) \) vanishes at the zero frequency, i.e.

\[
|\Psi(\omega)|^2 \bigg|_{\omega=0} = 0 \quad \ldots \ldots (5.7)
\]

It means that wavelets must have a band-pass like spectrum. The waveform of this proposed wavelet is shown in the Fig. 5.1.

This wavelet provides better Signal to Noise Ratio when compared to the other existing wavelets and used for both CWT and DWT operations. It also belongs to orthogonal family because the scaling coefficients and wavelet coefficients are orthogonal.
This wavelet is associated with the filter banks, which are required for the decomposition and reconstruction of signals. To design a wavelet with filter banks, it must satisfy the following condition

$$|f_0|^2 + |f_1|^2 = 1$$

If this condition is not met, the original signal can be decomposed, but it cannot be reconstructed back. The main purpose of filter bank is to calculate the lower resolution coefficients from the higher resolution coefficients. It also performs down sampling in the process of decomposition. For reconstruction, it performs the operation of filtering and up sampling. For better reconstruction of the signal decomposition levels are chosen suitably.

The execution of this proposed wavelet is possible only if this wavelet is included is in the existing wavelet family. The following details are provided to include this wavelet into wavelet family in MATLAB.
After providing the above details into the wavelet family, the ‘SVBSLET’ wavelet appears with in the list of family of wavelets.

5.4 VERIFICATION ANALYSIS OF ‘SVBSLET’

In order to remove the noise and pick up the original signal, it is attempted to perform the operation of de-noising and thresholding with the existing wavelets and with the ‘SVBSLET’ wavelet.

De-noising of the signal using ‘SVBSLET’ is also verified using Wavelet Shrinkage method. Wavelet shrinkage is also a signal Denoising technique based on the concept of thresholding the wavelet coefficients. Wavelet coefficients having small absolute value are considered to encode, mostly noise and very fine details of the signal. In contrast, the important information is encoded by the coefficients having large absolute value. Removing the small absolute value coefficients and then reconstructing the signal shall produce signal with lesser amount of noise.

In this method non linear soft thresholding of the signal is carried out in the wavelet transform domain. First, the data is
represented in terms of a wavelet basis, for which the coefficients that are below a certain threshold are set to zero and those above the threshold are shrunk by the value of threshold. The threshold determines the level of noise to be suppressed. Larger the variance of the noise, the larger should threshold value.

![Diagram of de-noising procedure using 'SVBSLET'](image)

After thresholding the detail coefficients using wavelet shrinkage method, the signal is reconstructed back. The reconstructed signal checked for its signal to noise ratio.

**5.5 PEAK SIGNAL TO NOISE RATIO**

Signal to Noise Ratio (SNR) method estimates the quality of a reconstructed signal by comparing it with its original signal. The basic idea is to compute a single number that reflects the quality of the reconstructed signal. Reconstructed signals with higher metrics are judged better.

The actual metric that is computed is the ratio of original peak signal-to-reconstructed peak signal, which is called Peak Signal to Noise Ratio (PSNR). Original signal source $f$ having $N$ by $N$ samples is reconstructed. The signal is reconstructed by
decoding the encoded version of f. The reconstructed signal is called F.

First the mean squared error (MSE) of the reconstructed signal shall be computed as given in eqn.5.8

\[ \text{MSE} = \frac{\sum (f - F)^2}{N^2} \quad \ldots \quad (5.8) \]

The Root Mean Squared Error (RMSE) is the square root of MSE. Some formulations use N rather than \( N^2 \) in the denominator for MSE. PSNR in decibels (dB) is computed by using the eqn.5.9

\[ \text{PSNR} = 10 \log_{10} \frac{[\text{MAX}_i^2]}{\text{[MSE]}} = 20 \log_{10} \frac{[\text{MAX}_i]}{[\text{N MSE}]} \quad \ldots \quad (5.9) \]

where \( \text{MAX}_i \) is the maximum value of the signal. More generally, when samples are represented using linear PCM with B bits per sample, maximum possible value of \( \text{MAX}_i \) is \( 2^B - 1 \).

**5.6 EXTRACTION OF HYDRAULIC OIL LEAKAGE SIGNAL**

AE data corresponding to hydraulic oil leakage is recorded during proof pressure testing of rocket motor hardware. This signal (test signal) is corrupted by random noise present at all instants of time. The useful signal is extracted from noisy signal as described below.

The acoustic emission signals due to hydraulic leak are typically low amplitude and low frequency signals enveloped by relatively high frequency background noise. So to de-noise the test signal, the detail coefficients are thresholded. In the present
work, all the detail coefficients, at all the levels, are made zero and the test signal is reconstructed back using the methodology explained in Chapter 4.

The same test signal is denoised using 'SVBSLET' wavelet and the signal is reconstructed. This reconstructed test signal is found to be better than the signal obtained from the other denoising methods using existing wavelets.

The signal is then verified further by employing the Double-density Discrete Wavelet Transformation (DWT) method. Here, by applying the Double-density DWT to the above data, decomposition operation takes place, where a set of wavelet coefficients are obtained. The suitable coefficients consist of details in the high frequency sub-bands. Based on the details obtained, the test signal is reconstructed. The signal obtained using 'SVBSLET' wavelet decomposition method and double density DWT is compared.

The signal extracted from the known noisy data using the 'SVBSLET' wavelet is matching with the original signal than with the signal extracted from other methods. The performance is thus validated and found satisfactory.

5.7 RESULTS OF 'SVBSLET'

Using the same test setup as discussed in chapter-4 a set of reference signatures corresponding to hydraulic leak are pre-recorded with out having any back ground noise. This data is
kept in the data base. This is done to validate the test data recorded during the actual proof pressure test.

Test data that are recorded during different proof pressure tests are categorized based on the types of noises present in the data.

i. Test data 1 (Fig.5.3): Presence of only random noise throughout the signal.

ii. Test data 2 (Fig.5.4): Hydraulic oil leakage signal that is buried in background noise.

iii. Test data 3 (Fig.5.5): Presence of heavy background noise.

The above test data are de-noised with different wavelets including the new 'SVBSLET' wavelet. The de-noised versions of the test data1 using various wavelets are shown in Fig.5.6. The subtle variations in the de-noised signals are due to different wavelets used. Denoising is carried out with all the available wavelets. By comparing the denoised signals with the reference signals, the best wavelets are chosen for denoising the test data. In the present work, test signals are de-noised using coif3, db8, bior3.9 and 'SVBSLET' wavelets which are having good match with the actual data.

The most appropriate de-noised signal is selected as required. If more than one de-noised signals is obtained from different wavelets, then their average is considered for further
analysis. The signal to noise ratio (SNR) is found to be better in the average de-noised signal.

Fig.5.7 and Fig.5.8 show the de-noised signal, obtained using different wavelets mentioned above, for the test data 2 and test data 3 respectively.

To check the performance of various wavelets, the noise levels are also checked. This is done by employing PSNR method. The values of SNR obtained after de-noising, for each wavelet corresponding to each test data are given in Table 5.1. From the table it can be noted that all the wavelets chosen for denoising yield a comparable SNR for all the three test data. Further the performance of new ‘SVBSLET’ wavelet is found to have a good match with the other wavelets.

Table 5.1 Noise levels of each test-data with various wavelets.

<table>
<thead>
<tr>
<th>Test Data</th>
<th>COIFLET WAVELET</th>
<th>BIORTHOGONAL WAVELET</th>
<th>DAUBECHIES WAVELET</th>
<th>SVBSLET WAVELET</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12.93</td>
<td>11.59</td>
<td>13.27</td>
<td>13.33</td>
</tr>
<tr>
<td>2</td>
<td>19.82</td>
<td>19.25</td>
<td>19.82</td>
<td>19.81</td>
</tr>
<tr>
<td>3</td>
<td>11.82</td>
<td>11.61</td>
<td>11.95</td>
<td>11.82</td>
</tr>
</tbody>
</table>

The test data 1 and its average denoised signal are shown Fig.5.9. From the plots it can be noted that the pattern is the signature corresponding to random noise.

The test data 2 and its average denoised signal are shown Fig.5.10. From the plots it can be noted that the pattern is the signature is corresponding to hydraulic oil leakage.
The test data 3 and its average denoised signal are shown Fig.5.11. From the plots it can be noted that the pattern is the signature corresponding noise.

Fig.5.12 show the effective de-noised signal for test data2 corresponding to hydraulic oil leakage. The signal is verified using Double-Density DWT method and found matching with the reference hydraulic leakage signature of the data base.

It is concluded that the hydraulic oil leakage signal can be easily extracted adopting the denoising method using 'SVBSLET' wavelet.

The signal analysis is done by developing a program using MATLAB Software.
Fig. 5.3 Test data1 - Random noise

Fig. 5.4 Test data2 - Hydraulic oil leakage with noise

Fig. 5.5 Test data3 - Heavy background noise
Fig. 5.6: Denoising of test data using various wavelets.
Fig. 5.7 De-noising of test data using various wavelets.
Fig. 5.8 De-noising of test data 3 using various wavelets.
Fig. 5.9 Test signature and denoised data for Test data1
Fig. 5.10 Test signature and denoised signal for Test data2
Fig. 5.11 Test signature and denoised signal for test data 3
Signal extraction using double-density DWT method.

The amplitude of the Acoustic Emission signal corresponding to leakage of hydraulic oil is very low and it is completely buried in the noise. As the existing wavelets are not suitable for signature identification of hydraulic oil leakage, a new wavelet 'SVBSLET' is developed and included in the wavelet family. The performance of this new wavelet is verified by wavelet shrinkage method and peak SNR method. The test data is analysed by denoising with the existing wavelets and also with 'SVBSLET' wavelet. Signal analysed with 'SVBSLET' wavelet identified the hydraulic oil leakage signal from the noisy data. With the inclusion of this new wavelet the requirement for signature identification all the events that can occur during the proof pressure testing of rocket motor hardware is completely met.