5.1 INTRODUCTION

One of the major advantages of a processor based analysis instrument over alternate systems (analogue, gate array based, etc.) is its ability in providing dynamic signal conditioning prior to parameter extraction. AEDAPS provides a number of possibilities in this respect, that may be classified as (a) conventional FIR and IIR filters, (b) mean / median smoothing and (c) profile extraction. This section describes the implementation, timing and utility issues of these facilities.

Section 5.2 describes the Digital Filtering facilities provided. The decision on which filter to be used for a specific application is beyond the scope of the instrument developer. Excellent references for this are [Parks & Burrus 1987], [Elliot 1987] and [Vaidyanathan 1993]. Generally, usage of IIR filters is recommended in all cases where the resulting non-linear phase response is acceptable to the investigation. Section 5.3 describes the facilities provided for signal smoothing with mean and median filters. These have been extensively studied in the literature, with the later recommended as an effective tool in removing certain types of noise ( "salt and pepper" , for egg.), prior to signal extraction. Section 5.4 describes an envelop extractor developed specifically for AEDAPS. It removes the effects of the transducer and brings out the overall shape of the AE signal and hence can be used for the estimation of shape related parameters like skew and kurtosis of the signal. In the processing chain this can stand alone or follow a previous smoothing function. The effect of this on the conventional AE parameters is brought out in section 5.5.

The facilities delineated herein have been used in a number of AE test sessions with rocket motor cases. The results of these tests are summarized in chapter 7.

The main conclusions of this chapter are the following:

• User specified digital filters could be set up within AEDAPS to filter out extraneous noise in all cases where there is an a-priori knowledge about the spectral characteristics of the noise.

• The median filtering does not seem to give any particular advantage to the AE tests evaluated. However, the tests considered were all in controlled environments. It is possible that the median filter turns out to be a very effective tool in industrial environments, wherein tight control of the environment is not feasible.

• The profile extraction subsequent to digital filtering has been found to give a smooth signal that can be used for the computation of a number of statistical parameters of the AE signal. From an intuitive view point, the profile is related to the source as well as the propagation aspects of the AE signal (the actual signal being the modulation of this profile by the transducer frequency). Hence the parameters based on the profile is expected to be more relevant to the physical entities under investigation. More study with controlled events can bring out this aspect.
5.2 DIGITAL FILTERING

Digital filtering is an effective signal massaging tool in cases where there is reason to believe that the AE signal could be corrupted by extraneous noise whose spectral characteristics are known a-priori [Pitas – 1988]. This section describes the Digital Filter functions provided along with AEDAPS. This is split into two subsections – viz. – implementation aspects and the effect of filtering on the AE signal.

5.2.1 Implementation aspects

The design of the filter is performed at the SAP side on the host PC and its realization is achieved in the DAP section of the DSP processor servicing the corresponding channel. Fig 5.1 gives the SAP side screen for invoking the Digital Filter.

Chebechev, Inv Chebychev, Elliptic, or Butterworth [Parks & Burrus 1987].

The filter type and the associated taps and weights are sent to the DSP by the “SetFilter” request and the actual filtering is subsequently enabled by the “DFEnable” request.

The filter weights are normalised at the design stage. The FIR filter implementation is achieved by repeated realization of the “Multiply and Accumulate” operation in the formula:

\[ Y_i = \sum_{j=1}^{n} f_i x_j \]  

\[ \sum_{i=1}^{n} f_i = 1 \]

Note that the operation is performed on the transformed data stream after companding. A “Multiply with accumulate” operation takes one cycle on the TMS320 and hence one filtering cycle takes \( N_{\text{hdt}} \) cycles. Assuming that the system is operating at its peak rate (10MHz) and the AE signal is flowing continuously, the DSP is definite to clog at 5 taps (20 ns Versus 100 ns sampling rate). In actual practice, the event duration is only a few percentage of the experimental duration, thereby allowing many more filter taps.

\[ F_{\text{maxtap}} \approx \frac{1}{f * R_{\text{active}}} \]

Where \( F_{\text{maxtap}} \) is the maximum filter taps for avoiding CPU clogging, \( f \) is the sampling rate and \( R_{\text{active}} \) is the ratio of the active to total time.

In the case of AEDAPS,

\[ f * R_{\text{active}} = N_{\text{events}} * N_{\text{hdt}} \]

where \( N_{\text{events}} \) is the number of events in the interval and \( N_{\text{hdt}} \) is the number of samples in the period specified by HDT. Hence, we have,

\[ F_{\text{maxtap}} \approx \frac{1}{(N_{\text{events}} * N_{\text{hdt}})} \]
Thus, the maximum filter taps possible is inversely proportional to the total number of events. Since the filter taps are to be determined ahead of the experimentation, it has to be replaced by its expectation and the above formula reduces to

\[ F_{\text{maxtap}} \propto \text{Exp(Event Rate)} \]

indicating that, in case we can assume quasi-stationarity for the event rate, processor load sharing for digital filtering could be achieved by dynamically allocating additional processors in cases where the current event rate exceeds the present digital filtering threshold.

Even though the above discussion was based on FIR filter only, the arguments are equally true in case of the IIR filters as well. Only the proportionality constant will change in this case.

### 5.2.2 Effects Of Digital Filtering On The AE Signal

The effect of filtering on a time domain signal sequence is well understood and is given in a number of references on the topic. [Rabiner & Gold 1975, Oppenheim & Schafer 1989].

We will start our discussion with a simple filter – an elliptical low pass filter with 4 taps, with a cut-off frequency of 200 KHz, and an attenuation of 40 dB. Fig 5.2 gives the time domain signal (magenta), on which the filtered signal (blue) is superimposed.

As expected, the filtering removes the ringing leaving the profile of the signal. Notice also that the signal strength is reduced.

The above filter may be compared with the “Max-Filter” described in section 4.4, the standard profile extractor used by the system. In this case the signal is replaced by the running maximum. Fig 5.2(b) gives the superimposed profile for this filter with 5 taps.

![Fig 5.2(b) : Max Filter with 5 taps on original Signal](image)

Note that the extractor consistently over-estimate the profile leaving a higher energy for the filtered signal than the original.
Fig 5.2(c) gives the output of the max-filter on the filtered output of the low pass filter given in Fig 5.2(a).

Not that the output is a better profile than either of 5.2(a) or 5.2(b). (It sort of brings back the lost energy in the smoothing process!). This is one reason why the DAP system uses this as the default scheme for profile extraction prior to sub-event determination.

Fig 5.2(d) gives the same signal with superimposed filtered output after filtering with a 30th order elliptical low pass filter at a cut-off frequency of 100 KHz, pass band ripple 0.5 dB and an attenuation of 60 dB.

Fig 5.3: Band-Pass Filter – 125-175 KHz

Since Digital filtering reduces the overall energy of the signal, the peak amplitude and consequently the number of events will be much lower compared to the original. Digital filtering can be effectively used to reduce external noise in many cases. One approach to this is providing a band pass filter with center frequency coinciding with the sensor resonant frequency. Fig 5.3 illustrates the effect in a typical case. The top plate gives the original signal and the bottom one after band pass filtering with a Butterworth filter with cut-off frequencies at 125 KHz and 175 KHz, and a 60 dB attenuation. Notice that unlike the case of Fig 5.2(d), there is no substantial energy reduction due to filtering. This is because the resonant frequency of the sensor was 150 KHz. The filtered signal is more AE-like. Hence, the sub-event demarcation algorithms will work much better with it than with the original.

Considering the effectiveness of the band pass filter to shape out the signal in noise, it is interesting to investigate the percentage loss of power due to this type of filtering. Section 7.4 of chapter 7 provides this analysis. In general, it is seen that when we use a band pass filter with center frequency coinciding with the resonant frequency of the sensor, the average reduction in the peak amplitude and the energy parameter is less than 4 dB.

Fig 5.2(d): Low-pass Filter - 100 KHz

Since the cut-off frequency is much smaller than the sensor resonant frequency, there is a dramatic decrease in the energy of the signal. As expected it has become much smoother.

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Fig 5.3: Band-Pass Filter – 125-175 KHz

Digital filtering will be effective in cases where we use a less sensitive broad-band sensor to investigate the final spectral aspects of the AE signal.

5.2.3 Implications of Digital Filtering in Event Rate and AE Parameters

Since Digital filtering reduces the overall energy of the signal, the peak amplitude and consequently the number of events will be...
Chapter 5 - Digital Filtering and Profile Extraction Using AEDAPS

reduced due to filtering. Hence digital filtering could be considered as an alternative to threshold increase for reducing the event rate in situations where the current system load is unsustainable (See chapter 3).

An analysis of the effect of digital filtering on the prominent AE parameters like peak amplitude, duration and energy is given in Chapter 7.

5.3 MEAN AND MEDIAN SMOOTIDNG

Even though the mean smoothing is a form of low pass FIR filtering (with equal weights), it is worth considering this separately, since the realization timing is very different. This is due to the algorithmic efficiency in its implementation. The algorithm removes the dependency on the tap-length from the implementation time.

The median smoothing has been found effective in many situations, but our analysis indicates that it is not particularly useful in the AE situation. This is further illustrated in 5.3.2

5.3.1 Mean Smoothing

Smoothing the signal with its running mean is FIR filtering with equal tap weights. However, instead of a repeated multiply accumulate operation, we implement this by maintaining the running sum by subtracting the least recent value from it and adding the most recent one. This removes the relation of filter taps from the computation time required for smoothing.

The other major difficulty with conventional implementation is that the filter will give very unstable output in areas where there is strong AE activity, whenever the filter size exceeds \( \eta \), given by:

\[
(5.7) \quad \eta = \frac{f}{2f_0}
\]

where \( f \) is the sampling frequency and \( f_0 \) is the sensor resonant frequency. This is because, beyond these filter lengths, the ringing due to the resonant sensor makes the positive and negative peaks within the signal to cancel each other leaving an unstable residue as the filter output. The effect is best illustrated in Fig 5.4 that shows the original signal and its spectrum along with smoothed signal with 5, 10 and 15 taps and their spectrum.

Fig 5.4(a) shows the original signal (magenta) and the effect of smoothing it with a 5 tap mean filter (blue). The sampling frequency in this case was 2500 KHz and the sensor resonant frequency 150 KHz giving \( \eta = 8 \). Note that the energy of the filtered signal has not reduced appreciably, but the spectral shape has changed substantially. The intensity of the spectrum at resonant frequency is reduced by a factor of 5 making the nearest peak at 100 KHz below it appear equally prominent. As expected, there is a sharp cut-off at the high frequency segments.
In practical real-time situations where the mean smoothing is preferred to band pass filtering due to its algorithmic efficiency, the severe limitation on the tap length given by (5.7) can turn out to be a major problem. To circumvent this, AEDAPS allows the filtering to be done on the absolute value of the signal, which makes the filtered output stable and smooth. Fig 5.5 gives the output of this operation with 15 taps for the signal indicated in Fig 5.5.

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These effects are more prominent in Fig 5.4(c) that shows the signal and its spectrum after mean filtering with 15 taps. Note that the signal is almost vanishing and the spectral shape has changed substantially.

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Comparing 5.5 and 5.6, we can see that the latter profile is smoother and qualitatively more pleasing than the former.

5.3.2 Median Smoothing

Conventionally median smoothing is used to remove uncorrelated noise with random amplitude. This type of noise is quite jerky and the amplitudes can be very high. Mean smoothing will smear in this high amplitudes into the smoothed signal. This could be avoided if the running mean is replaced by the running median, since the latter is unaffected by the extreme values in the running sequence [Miller & Freund 1987].

Fig 5.7 below gives the effect of median smoothing on the signal considered in Fig 5.4.

![Fig 5.7(a) : Original Signal superimposed with filtered output with 5 tap median filtering (top plate), and spectrum of filtered signal (bottom plate).](image)

5.7(a) gives the signal and spectrum corresponding to median smoothing with 5 taps. Comparing this with the corresponding figures in 5.4, it is clear that the median smoothing is not very appropriate in the AE situation. The instability brought in by the ringing within the signal is more pronounced in this case. (Note that the strength of the spectral peak is reduced three fold). Fig 5.7(b) giving the situation corresponding to 10 taps makes this aspect abundantly clear.

As in the case of mean-smoothing, filtering the absolute signal removes the instability. Fig 5.8 and 5.9 gives the outputs corresponding to Fig 5.5 and 5.6.

![Fig 5.8 : Median Filtering with 15 taps on absolute signal](image)

It can be seen that the outputs are comparable. Since the median smoothing is computationally more involved than the mean smoothing, there
is no particular advantage for using this in the case of AE extraction. However, in case there is reason to suspect that the signal is corrupted with "salt and pepper noise", the median filter may be chosen instead of the mean filter prior to profile extraction [Elliot 1987].

Fig 5.9: Profile extracted using Max-filter on signal indicated in 5.8