Computationally Efficient Adaptive Rate Sampling and Filtering

Saeed Mian Qaisar, Laurent Fesquet, Marc Renaudin
TIMA, CNRS UMR 5159, 46 avenue Felix-Viallet, 38031 Grenoble Cedex
{saeed.mian-qaisar, Laurent.fesquet, marc.renaudin}@imag.fr

ABSTRACT

This paper is a contribution to enhance the signal processing chain required in mobile systems. The system must be low power as it is powered by batteries. Thus a signal driven sampling scheme based on level crossing is employed, adapting the sampling rate and so the system activity by following the input signal variations. In order to efficiently filter the non-uniformly sampled signal obtained at the output of this sampling scheme a new adaptive rate FIR filtering technique is devised. The idea is to combine the features of both uniform and non-uniform signal processing tools to achieve a smart online filtering process. The computational complexity of the proposed filtering technique is deduced and compared to the classical FIR filtering technique. It promises a significant gain of the computational efficiency and hence of the processing power.

1. CONTEXT OF THE STUDY

The motivation of this work is to contribute in the development of smart mobile systems. The goal is to reduce their size, cost, power consumption, processing noise and electromagnetic emission. This can be done by smartly reorganizing their associated signal processing theory and architecture. The idea is to combine the signal event driven processing with the clock less circuit design in order to reduce the system dynamic activity. Mostly the systems are processing signals with interesting statistical properties, but the Nyquist signal processing architectures do not take full advantage of such properties. These systems are highly constrained due to the Shannon theory especially in the case of signals such as electro-cardiograms, speech, seismic signals etc. which are almost always constant and vary sporadically only during brief moments. This condition causes a large number of samples without any relevant information, a useless increase of system activity and so a useless increase of system power consumption. This problem can be resolved by employing a smart sampling scheme, captures only the relevant information from the incoming signal. The idea is to realize a signal event driven sampling scheme, based on signal amplitude variations. This sampling scheme drastically reduces the activity of the post processing, analysis or communication chain because it only captures the relevant information. It is based on "level-crossing" that provides a non-uniform time repartition of the samples. In this context an AADC (Asynchronous Analog to Digital Converter) [2] based on LCSS (Level Crossing Sampling Scheme) [1] has been designed. Algorithms for processing [3 & 6] and analysis [7 & 8] of the non-uniformly spaced out in time sampled data obtained with AADC have also been developed. The focus of this work is to develop an efficient FIR filtering technique. The idea is to adapt the sampling rate and the filter order by following the variations of the incoming signal. An efficient solution is proposed by combining the features of both non-uniform and uniform signal processing tools.

2. LCSS (LEVEL CROSSING SAMPLING SCHEME)

The LCSS has already been studied by Jon W. Mark [1]. In [4], authors have shown that ADC based upon LCSS has a reduced activity and thus allows power saving and noise reduction compared to Nyquist ADCs.

An *M-bit* resolution AADC has $2^M - 1$ quantization levels which are disposed according to the input signal amplitude dynamics. In the studied case the quantization levels are regularly spaced. A sample is captured only when the input analog signal ($x(t)$) crosses one of these predefined levels. The samples are not uniformly spaced in time because they depend on the signal variations as it is clear from Figure 1.

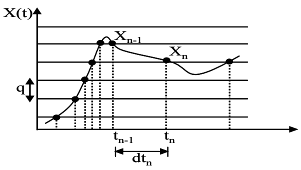

Figure 1: Level-crossing sampling scheme

A condition for proper reconstruction of non-uniformly sampled signals has been discussed in [5].In [5], Beutler showed that the reconstruction of an original continuous signal is possible, if the average sampling frequency $\overline{F}$ of the non-uniformly sampled signal is greater than twice of the input signal bandwidth (f_{max}). This condition can be expressed mathematically by $\overline{F} > 2f_{\max}$. According to [2], in the case of LCSS, the number of samples is directly influenced by the resolution of AADC. For an *M-bit* resolution AADC, the average sampling frequency of a signal can be calculated by exploiting its statistical characteristics. Then an appropriate value of *M* can be chosen in order to respect the Beutler's criterion.

3. PROPOSED FILTERING TECHNIQUE

Block diagram of the proposed filtering technique is shown in Figure 2. This technique is splitted into two filtering cases explained in Sections 3.3.1 and 3.3.2 respectively.

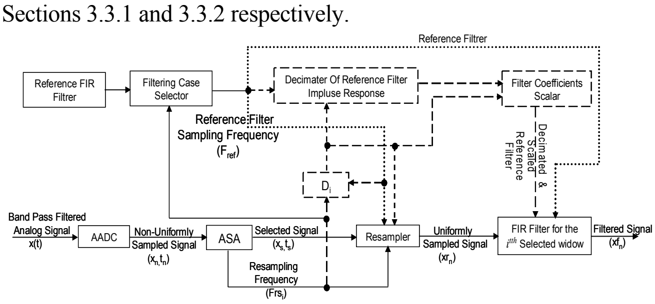

Figure 2: Block Diagram of the proposed filtering technique, '——' represents the common blocks and signal flow used in both filtering cases, '……' represents the signal flow used only in case 1 and '----' represents the blocks and signal flow used only in case 2

3.1. AADC + ASA

For a non-uniformly sampled signal obtained at the output of an AADC, the sampling instants (according to [1]) are defined by Equation 1.

$$t_n = t_{n-1} + dt_n \,. \quad (1)$$

In Equation 1, t_n is the current sampling instant, t_{n-1} is the previous one and dt_n is the time delay between the current and the previous sampling instant, as shown in Figure 1.

Let δ be the processing delay of AADC for one sample point. For proper signal acquisition the $x(t)$ must satisfy the "tracking condition" [2] given by Expression 2. In Expression 2, q is the quantum of AADC and is defined by Equation 3.

$$\frac{dx(t)}{dt} \le \frac{q}{\delta} \,. \quad (2) \qquad q = \frac{\Delta x(t)}{2^M - 1} \,. \quad (3)$$

In Equation 3, $\Delta x(t)$ represents the amplitude dynamics of $x(t)$ and M represents the resolution of AADC. AADC has a finite bandwidth so in order to respect the Beutler's criteria [5] and the tracking condition [2], a band pass filter with pass-band $[f_{min} \,;\, f_{max}]$ is employed at the input of AADC.

The relevant (active) parts of the non-uniformly sampled signal are selected and windowed by ASA (Activity Selection Algorithm). This algorithm has been implemented by employing the values of dt_n (Equation 1). The complete procedure of activity selection has been explained in [8]. ASA displays interesting features with LCSS which are not available in the classical case. It correlates length of the selected window with the signal activity. In addition, it also provides an efficient reduction of the phenomenon of spectral leakage in case of transient signals. This is done by minimizing the signal truncation problem with a simple and efficient algorithm instead of a smoothening window function (used in the classical scheme) [8].

3.2. Adaptive Rate Sampling

In case of AADC the sampling is triggered when the input signal crosses one of the pre-specified threshold levels. As a result, the temporal density of the sampling operation is correlated to the input signal variations. The relevant signal parts are locally over-sampled in time [3]. More the signal varies rapidly more it crosses thresholds in a given time period. This is the reason of local over-sampling in time of relevant signal parts. Contrary no sample is taken for the static signal parts. The approach is especially well suited for the low activity sporadic signals. Hence for such kind of signals the average sampling frequency remains less than the required sampling frequency for the classical scheme, performing the same operation. This smart sampling reduces the system activity and at the same time improves the accuracy of signal acquisition.

ASA selects and windows relevant parts of the non-uniformly sampled signal obtained at the output of AADC. The selected data obtained at the output of ASA can be used directly for further digital processing. However in the studied case it is required to uniformly resample the selected data. So there will be an additional error due to this transformation. Nevertheless, prior to this transformation, one can take advantage of the inherent over-sampling of the relevant signal parts in the system. Hence it adds to the accuracy of post-resampling process. The NNR (nearest neighbour resampling) interpolation is employed for data resampling. The reasons of inclination towards NNR interpolation are discussed in [8 & 11].

The resampling frequency (Frs_i) of each selected window obtained at the output of ASA can be specific depending upon the window length (in seconds) and the signal slope lying within this window [8]. The value of Frs_i for the i^{th} selected window can be calculated by using the following equations.

$$Ts_i = t\max_i - t\min_i \,. \quad (4) \qquad Frs_i = \frac{N_i}{Ts_i} \,. \quad (5)$$

In Equation 4, $tmax_i$ and $tmin_i$ are the final and the initial times of the i^{th} selected window. These parameters describe the window length (Ts_i) in seconds. In Equation 5, N_i is the number of samples lying in the i^{th} selected window, depends upon the signal slope lying within this window [8].

3.3. Adaptive Rate Filtering

The proposed filtering technique is a smart alternative of the multirate filtering [9 & 10]. It achieves computational efficiency which is not attainable with the classical FIR filtering.

It is known that for fixed design parameters (cut-off frequency, transition-band width, pass-band and stop-band ripples) the FIR filter order varies as a function of the operational sampling frequency. For high sampling frequency the order is high and vice versa. Thus computational gain can be achieved by adapting the sampling frequency and the filter order by following the input signal variations.

In the classical signal processing the input signal is sampled at a fixed sampling frequency, regardless of its activity. A unique (fixed order) FIR filter is employed to filter this sampled signal. Contrary in case of the proposed filtering technique the sampling frequency and the filter order both are adapted by following the incoming signal variations. The computational gain over the classical filtering is achieved by realising the adaptive rate sampling (only relevant samples to process) along with the adaptive filter order (only relevant number of operations per output sample).

The idea is to offline design a reference FIR filter by taking into account the incoming signal statistical characteristics and the application requirements. In the studied case the reference filter is designed by taking into account the bandwidth (f_{max}) of $x(t)$. The reference filter is designed for a reference sampling frequency (F_{ref}), satisfying the Nyquist criteria for $x(t)$. It can be expressed mathematically by Expression 6.

$$F_{ref} \ge 2 \times f_{\max} \,. \quad (6)$$

The reference filter impulse response (h_k) is sampled at F_{ref} during offline processing. Here k represents the index of the reference filter coefficients. F_{ref} and the resampling frequency of the i^{th} selected window (Frs_i) should match in order to perform a proper filtering operation. During online processing F_{ref} and Frs_i remain the same if they are already equal. Otherwise, the difference between F_{ref} and Frs_i leads to two different filtering cases, explained below. The combine flowchart of both filtering cases is shown in Figure 3.

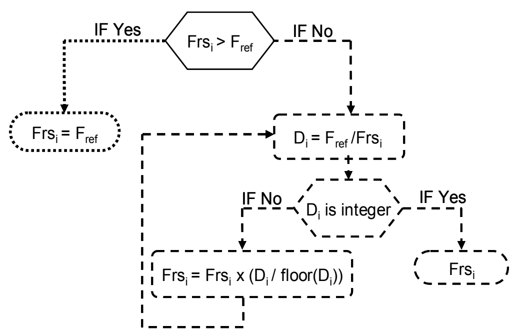

Figure 3: Combine flowchart of both filtering cases, '——' represents the common block used in both cases, '……' represents the block and signal flow only used in case 1 and '-----' represents the blocks and signal flow only used in case 2

3.3.1. Filtering case 1

This case is true if Frs_i is greater than F_{ref}. In this case F_{ref} remains the same and Frs_i is decreased to match it to F_{ref}. For case 1, Frs_i (calculated by Equation 5) is higher than the overall Nyquist frequency of $x(t)$. The upper limit on the Frs_i is employed by the Bernstein's inequality [2], given by Expression 7. In Expression 7, $\Delta x(t)$

is the amplitude dynamics of $x(t)$. Here $\Delta x(t)$ is adapted to match to the amplitude range of AADC. The term on left hand side is the slope of $x(t)$ and f_{max} is the bandwidth of $x(t)$. Thus for an *M-bit* resolution AADC the highest sampling frequency (Fs_{max}) occurs for a pure sinusoid of frequency f_{max} and amplitude $\Delta x(t)$ and can be calculated by employing Equation 8.

$$\frac{dx(t)}{dt} \leq 2.\pi.\Delta x(t).f_{\max} \cdot \quad (7) \qquad Fs_{\max} = 2.f_{\max}.(2^{M}-1) \cdot \quad (8)$$

Fs_{max} applies the upper limit on Frs_i. Once the data is sampled by AADC and windowed by ASA, Frs_i can be reduced by simply assigning $Frs_i = F_{ref}$. This is done in order to resample the selected data lying in the i^{th} selected window closer to the Nyquist frequency. It avoids the unnecessary interpolations during the data resampling process of the i^{th} selected window. It also avoids the processing of unnecessarily samples from the system. Therefore improves the computational gain of the proposed filtering process.

3.3.2. Filtering case 2

This case is valid if F_{ref} is greater than Frs_i. In this case it appears that the data lying in the i^{th} selected window may be resampled at a frequency which is less than the overall Nyquist frequency of $x(t)$.Therefore it can cause aliasing. The sampling rate of AADC varies according to the slope of $x(t)$. A high frequency signal part has a high slope and AADC samples it at a higher rate. Hence a signal part with only low frequency components can be sampled by AADC at an overall sub-Nyquist frequency of $x(t)$. But still this signal part is locally over-sampled in time with respect to its local bandwidth. This statement is valid as far as the amplitude dynamics of this signal part are adapted to match the amplitude range of AADC. It makes the relevant signal part to usually cross all thresholds (more than one) of AADC so it is locally over-sampled in time. This statement is further illustrated with the results summarised in Table 3. Hence there is no danger of aliasing when the low frequency relevant signal parts are locally over-sampled at overall sub-Nyquist frequencies.

In case 2, h_k is decimated in order to keep the sampling frequency of the decimated filter coherent with Frs_i. The decimation factor D_i can be specific for each selected window depending upon Frs_i. Various methods can be adapted to deal with the fractional D_i and to keep the sampling frequency of the decimated filter coherent with Frs_i. The employed method is depicted in Figure 3.

From Figure 3 it is clear that D_i and Frs_i are correlated. First D_i is calculated by using Frs_i. Then a decision is made on the basis of D_i, weather an adjustment of Frs_i is required or not. If D_i is an integer keep the same Frs_i. If D_i is not an integer, make an increment in Frs_i depending upon the fractional part of D_i and then the D_i is recalculated for this new Frs_i. This fulfils both above stated goals of keeping D_i as an integer and the sampling frequency of the decimated filter coherent with Frs_i.

A simple decimation leads to a reduction of filter's energy which will lead to an attenuated version of the filtered signal. D_i is a good approximate of ratio between energy of the original (reference) filter and of the decimated filter (decimated for the i^{th} selected window). Hence this effect of decimation is compensated by scaling the coefficients of the decimated filter with D_i.

The process of obtaining the decimated and scaled filter for the i^{th} selected window from the reference one is shown mathematically by Equations 9 and 10.

$$hd_{i,j} = h_{D_i k} \cdot \quad (9) \qquad hw_{i,j} = hd_{i,j} \times D_i \cdot \quad (10)$$

According to Equation 9 the decimated filter impulse response ($hd_{i,j}$) for the i^{th} selected window is obtained by picking every D_i^{th} coefficient from the reference filter impulse response (h_k). Here k and j represents the indexes of the impulse responses of the reference filter and of the decimated filter respectively. If the length of h_k is A then the length of $hd_{i,j}$ is $P_i = A/D_i$. The process of scaling the $hd_{i,j}$ in order to obtain the decimated and scaled impulse response ($hw_{i,j}$) for the i^{th} selected window is clear from Equation 10.

4. ILLUSTRATIVE EXAMPLE

In order to illustrate the proposed filtering technique an input signal shown on the left part of Figure 4 is employed. Its total duration is 20 seconds and consists of three active parts. The summery of signal active parts is given in Table 1.

Active Part	Signal Components	Length (Sec)
First	0.5.sin(2.π.20.t) + 0.4.sin(2. π.1000.t)	0.5
Second	0.45.sin(2. π.10.t) + 0.45.sin(2. π.150.t)	1.0
Third	0.6.sin(2. π.5.t) + 0.3.sin(2. π.100.t)	1.0

Table 1: Summary of the input signal active parts

Table 1 shows that the input signal is band limited up to 1 kHz. This signal is sampled by employing a 3-bit resolution AADC. As $M = 3$ so the highest possible sampling frequency (Fs_{max}), calculated by Equation 8 is 14 kHz.

The non-uniformly sampled signal obtained with AADC is selected and windowed by ASA. For this example the reference (initial) window length is chosen equal to 1 second [8]. The three selected windows obtained with ASA, centred on each active part of the input signal are shown on the right part of Figure 4.

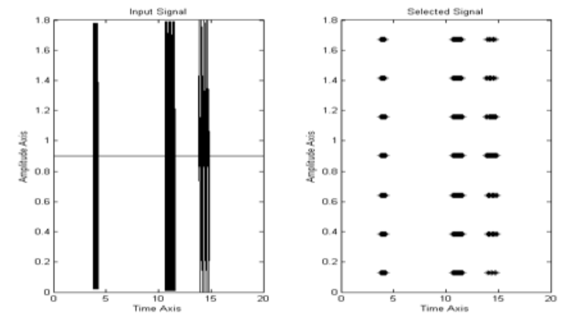

Figure 4: Input signal (left) and the selected signal (right)

Table 1 shows that each active part of the signal has a low and high frequency component. In order to filter the high frequency component of each signal activity a low pass reference FIR filter is implemented by using the standard Parks-McClellan algorithm. The reference filter parameters are given in Table 2.

Cut-off Freq (Hz)	Transition Band (Hz)	Pass Band Ripples	Stop Band Ripples	F_{ref} (Hz)	A
30	30~80	-25 (dB)	-80 (dB)	2500	127

Table 2: Summary of the reference filter parameters

In Table 2, A represents the order of the designed reference filter. F_{ref} is the reference sampling frequency for which the reference filter is designed. As $x(t)$ is band limited to 1 kHz so the F_{ref} is chosen equal to 2.5 kHz in order to satisfy the condition given by Expression 6.

Parameters of each selected window, obtained with ASA are summarized in Table 3.

Selected Window	Ts_i (Sec)	N_i (Samples)	Frs_i (Hz)	F_{ref} (Hz)	Filtering case
First	0.4998	3000	6000	2500	1
Second	0.9995	1083	1083	2500	2
Third	0.9992	460	460	2500	2

Table 3: Summary of parameters of each selected window

Table 3 exhibits the interesting features of the proposed filtering technique. N_i and Frs_i represent the sampling frequency adaptation by following the slope of $x(t)$. It is achieved due to the smart features of AADC and ASA. It is also clear from N_i that the relevant signal parts are over-sampled locally in time like any harmonic signal [3].

Ts_i in Table 3 exhibits the dynamic feature of ASA which is to correlate the reference window length with the signal activity lying in it. Contrary in the classical case, the windowing process does not select only the active parts of the sampled signal. Moreover the reference window length remains static and is not able to adapt according to the signal activity lying within the window. For this studied example the reference window length is chosen equal to 1 second. Hence in the classical case, it will lead to twenty 1-second windows for the whole signal span (20 Sec). It follows that the system has to process more than the relevant information part.

The decimation factor (D_i), the filter order (P_i) and the adjusted resampling frequency (Frs_i), for each selected window is summarized in Table 4.

Selected Window	Filtering case	Frs_i (Hz)	Adjusted Frs_i (Hz)	D_i	P_i
First	1	6000	2500	x	127
Second	2	1083	1250	2	64
Third	2	460	500	5	26

Table 4: D_i, P_i and adjusted Frs_i, for the i^{th} selected window

For the 1^{st} selected window filtering case 1 is valid. So Frs_1 is reduced by assigning $Frs_1 = F_{ref}$. This reduction of Frs_1 has two following benefits. First it avoids the needless interpolations during the data resampling process of the 1^{st} selected window. Secondly it avoids the processing of excessive samples from the system. Hence it adds to the computational efficiency of the proposed filtering technique. In case 1, h_k remains unaltered so there is no need to calculate D_1.

For the 2^{nd} and the 3^{rd} selected windows the filtering case 2 is valid. So h_k is decimated with D_2 and D_3 for the 2^{nd} and the 3^{rd} selected windows respectively. P_2 and P_3 in Table 4 represent the adaptation of reference filter order for the 2^{nd} and the 3^{rd} selected windows. D_2 and D_3 are used later on to scale the impulse responses of decimated filters $hd_{2,j}$ and $hd_{3,j}$ respectively. This scaling is applied to keep the energy of decimated filters at the same level to that of the original (reference) filter. The adaptation of h_k for the 2^{nd} and the 3^{rd} selected windows is another advantage of the proposed technique. It is achieved due to the appealing feature of ASA. Contrary, in the classical case the filter remains time invariant and has to be designed for the worst situation. In this example the input signal is band limited to 1 kHz. Therefore if the sampling frequency is chosen equal to 2.5 kHz in order to respect the Shannon theorem then for the same filter parameters (Table 2), Parks-McClellan algorithm design gives a 127^{th} order FIR filter. In the classical case the signal is sampled at a fixed sampling frequency (2.5 kHz), regardless of its activity. Hence a fixed order filter ($H = 127$) is employed for the whole signal span. That causes a useless system activity.

The activity lying in the 3^{rd} selected window is filtered by applying the proposed filtering technique and the classical one. In order to make a comparison of filtering quality the spectra of filtered signals obtained with the proposed and the classical filtering techniques are calculated. Spectra of the filtered signals and their zooms obtained with the proposed and the classical filtering techniques are shown in the left and the right parts of Figure 5 respectively.

Figure 5 shows that a relative error of 0.4% occurs between the results obtained with the proposed and the classical filtering techniques. It shows that for the 3^{rd} selected window decimation of the reference filter leads to a loss of quality. The measure of this quality loss can be used to decide the upper bound on the decimation factor (D_i). By performing offline calculations the maximum value of D_i can be decided for which the decimated and scaled filter provides filtering with an acceptable level of accuracy. The level of accuracy is application dependent.

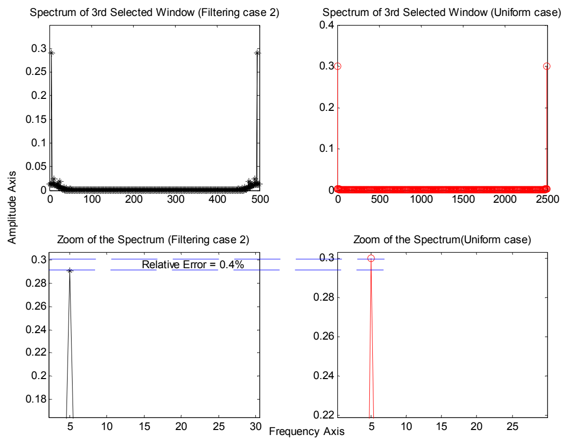

Figure 5: Spectrum of the filtered signal and its zoom obtained with the proposed filtering technique (top and bottom left respectively) and obtained with the classical filtering technique (top and bottom right respectively)

5. COMPUTATIONAL COMPLEXITY

This section compares the computational complexity of the proposed filtering technique with the classical one. The complexity evaluation is made by considering the number of online operations executed to perform the algorithm.

It is known that in the classical case the incoming signal is sampled at a fixed sampling frequency. In this case a time invariant, fixed order filter is employed to filter the sampled data. As for an H order FIR filter, H multiplications and H additions are computed for each output sample. The total computational complexity C_1 for N_u (number of uniform) samples can be calculated by employing Equation 11.

In the proposed filtering technique, the sampling frequency and the filter order both are not fixed and are adapted for each selected window according to the slope of $x(t)$. In comparison to the classical case this approach locally requires some extra operations in each selected window.

Filtering case selection is the first online operation performed by the proposed filtering technique. It requires one comparison between F_{ref} and Frs_i. If case 1 is true then the reference filter impulse response (h_k) remains the same. Contrary in case 2, h_k is decimated. The data resampling operation is required in both cases before filtering. In case 1, resampling is performed at a reduced Frs_i. On the other hand in case 2, it is performed at the same or an increased Frs_i (recall Figure 3). The NNR interpolator is employed to resample the non-uniform selected data. This interpolator requires only a comparison operation for each resampled observation. Therefore the interpolator performs N_i comparisons, where N_i represents the total number of samples lying in the i^{th} selected window.

In addition to this, filtering case 2 requires some additional operations. In case 2, it is required to decimate h_k. Therefore D_i is calculated for the i^{th} selected window. The calculation of D_i requires seven operations for the worst situation, three divisions, one multiplication, two comparisons and one floor operation as shown in Figure 3. In order to make a complexity comparison the operation count for the worst situation is taken into account. Decimation process of the reference filter for the i^{th} selected window has a negligible complexity as compare to operations like addition or multiplication. This is the reason that the complexity of the decimator is not taken into consideration. Moreover, it is required to scale the impulse response of the decimated filter by D_i. The filter coefficients scalar performs P_i multiplications; here P_i represents the order of the decimated filter for the i^{th} selected window. The combined computational complexity C_2 of the proposed filtering technique for both filtering cases is given by Equation 12.

$$C_1 = \underbrace{H.N_u}_{Additions} + \underbrace{H.N_u}_{Multiplications} \cdot \quad (11)$$

$$C_2 = \underbrace{3}_{Divisions} + \underbrace{1}_{Floor} + \sum_{i=1}^{L} \underbrace{(N_i+3)}_{Comparisons} + \underbrace{P_i.N_i}_{Additions} + \underbrace{(P_i.N_i+\beta.P_i)}_{Multiplications} \cdot \quad (12)$$

In Equations 12, β is a multiplying factor and its value is 0 for case 1 and 1 for case 2. The parameter $i = \{1, 2, 3, ..., L\}$ represents the index of the selected window. The computational gain of the proposed filtering technique over the classical one can be calculated by employing Equation 13.

$$G = \frac{C_1}{C_2} = \frac{H.N_u + H.N_u}{3+1+\sum_{i=1}^{L}(N_i+3)+P_i.N_i+(P_i.N_i+\beta.P_i)} \cdot \quad (13)$$

From Equations 11 and 12 it is clear that addition and multiplication are the common operations between the classical and the proposed filtering techniques. The operations like comparison, division and floor are uncommon between them and are required only in the proposed filtering technique. Because of these uncommon operations the computation comparison between the proposed and the classical filtering techniques is not straightforward. In order to make them approximately comparable the following assumptions are made.

*****Comparison has same processing cost as that of an addition.*

*****Division and floor operations are very small in number as compare to the addition, multiplication and comparison operations, so can be ignored during computation evaluation.*

By following these assumptions, comparisons are merged into additions and divisions and floor are neglected during the complexity evaluation process.

The computational gain of the proposed filtering technique over the classical one is calculated for the results of illustrative example, for different time spans of *x(t)*. The results are summarized in Table 5.

Time Span (Sec)	Gain in Additions	Gain in Multiplications
Ts_1	1.98	2
Ts_2	3.90	3.97
Ts_3	23.5	24.42
Total signal span (20)	24.9	25.2

Table 5: Summary of processing gain of the proposed filtering technique over the classical one

The adjusted value of Frs_1 is equal to the sampling frequency in the classical case (Table 4). Yet 1.9 & 2 times gains are achieved in additions and multiplications respectively, for the 1^{st} selected window. This is due to the dynamic feature of ASA which is to correlate the window length with the signal activity lying in it (0.5 Sec). Contrary, in the classical case the window length remains static (1 Sec) and system has to process extra samples.

Table 5 shows 24.9 & 25.2 times gains in additions and multiplications respectively for the whole signal span (20 sec). This gain is achieved by employing the joint benefits of AADC, ASA and resampling. As they allow to adapt the sampling frequency and the filter order by following the incoming signal variations.

6. CONCLUSIONS

A new adaptive rate filtering technique is proposed. This technique is well suited for low activity sporadic signals like electrocardiograms, speech, seismic signals, etc. A reference filter is designed offline by taking into account the input signal bandwidth and the application requirements. The proposed technique is splitted into two filtering cases. A complete methodology of firstly choosing the appropriate filtering case for the i^{th} selected window and then adjusting Frs_i or h_k depending upon the validity of case 1 or case 2 respectively has been demonstrated. It shows how the data resampling rate or the reference filter order is smartly adapted for each selected window by following the input signal variations. The computational complexity of the proposed adaptive rate filtering technique is deduced collectively for both filtering cases. A method to make an approximate computation comparison between the proposed and the classical filtering techniques is described. The comparison is made by using the results of an illustrative example. The results show 24.9 times gain in additions and 25.2 times gain in multiplications of the proposed filtering technique over the classical one. It shows that the proposed filtering technique leads to a significant reduction of the total number of operations. This reduction in operations is achieved by combining the adaptive rate sampling (reduce the number of samples to process) along with adaptive rate filtering (reduce the number of operations per output sample).

The decimation of reference filter is required in filtering case 2. The complete procedure of decimating and scaling the pre-calculated reference filter during online computation is demonstrated. The decimation of reference filter reduces the quality of the decimated filter as compared to the reference one. The upper bound on decimation factor can be determined by offline calculations, for which the decimated and scaled filter gives response with an acceptable level of accuracy. Moreover for applications where high quality filtering is required, an appropriate filter can be calculated directly online for each selected window at the cost of an increased computational load.

REFERENCES

[1] J.W. Mark and T.D. Todd, "A nonuniform sampling approach to data compression" IEEE Transactions on Communications, vol. COM-29, pp. 24-32, January 1981.

[2] E. Allier, G. Sicard, L. Fesquet and M. Renaudin, "A new class of asynchronous A/D converters based on time quantization", ASYNC'03, pp.197-205, Vancouver, B.C, Canada, May 2003.

[3] F. Aeschlimann, E. Allier, L. Fesquet and M. Renaudin, "Asynchronus FIR filters, towards a new digital processing chain", ASYNC'04, pp. 198-206, Crete, Greece**,** April 2004.

[4] N. Sayiner, H.V. Sorensen and T.R. Viswanathan, "A Level-Crossing Sampling Scheme for A/D Conversion", IEEE Transactions on Circuits and Systems II, vol. 43, pp. 335-339, April 1996.

[5] F.J. Beutler, "Error free recovery from irregularly spaced samples", SIAM Review, vol. 8, pp. 328-335, 1996.

[6] S. M. Qaisar, L. Fesquet, M. Renaudin "Adaptive rate filtering for a signal driven sampling scheme", ICASSP'07, April 15-20, 2007, Honolulu, Hawaii, USA.

[7] F. Aeschlimann, E. Allier, L. Fesquet and M. Renaudin "Spectral analysis of Level Crossing Sampling Scheme", International Workshop on Sampling theory and application SAMPTA, Samsun, Turkey, 10-15 July 2005.

[8] S. M. Qaisar, L. Fesquet, M. Renaudin "Spectral analysis of a signal driven sampling scheme", EUSIPCO 2006, September 4-8, 2006, Florance Italy.

[9] Shuni Chu, Burrus, C. "Multiate filter designs using comb filters", IEEE transaction on Circuits and Systems, vol. 31, PP. 913-924, November 1984.

[10] M. Vetterli, M. "A theory of multirate filter banks", IEEE transaction on Acoustic, Speeh and Signal Processing, vol. 35, March 1987.

[11] S. de Waele and P.M.T.Broersen "Time domain error measures for resampled irregular data", IEEE Transactions on Instrumentation and Measurements, pp.751-756, Venice, Italy, May 1999.