Event Driven Filtering an Intelligent Technique for Activity and Power Consumption Reduction

Dr. Saeed Mian Qaisar

***Abstract*—**This work is a contribution to enhance the signal processing chain required in remote systems like mobiles, biomedical implants, satellites, etc. The system is powered by a battery therefore it must be power efficient. Filtering is a basic operation, almost required in every signal processing system. The classical filtering is time-invariant, the sampling frequency and the filter order remains unique. Therefore it can render a useless increase of the processing activity, especially in the case of sporadic signals. In this context an adaptive rate filtering technique, based on an event driven sampling is devised. It adapts the sampling frequency and the filter order by analysing the input signal characteristics. It correlates the processing activity to the signal variations. The computational complexity and the output quality of the proposed technique are compared to the classical one for a speech signal. Results show a drastic computational gain, of the proposed technique compared to the classical one, along with a comparable output quality.

***Keywords*—** Event driven filtering, Event driven sampling, Activity selection, Low power consumption, Computational efficiency, Processing error.

I. INTRODUCTION

THIS work is part of a large project aimed to enhance the signal processing chain implemented in the mobile systems. The motivation is to reduce their size, cost, processing noise, electromagnetic emission and especially power consumption, as they are most often powered by batteries. This can be achieved by intelligently reorganizing their associated signal processing theory and architecture. The idea is to combine event driven signal processing with clock less circuit design, in order to reduce the system processing activity and energy cost.

The motivation of this work is to achieve an efficient FIR (Finite Impulse Response) filtering technique. The idea is to adapt the sampling frequency and the filter order by following the input signal characteristics variation. In this context, an efficient solution is proposed by combining features of both non-uniform and uniform signal processing tools. It assures a drastic computational gain of the proposed technique compared to the classical one.

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Dr. Saeed Mian Qaisar has received his Masters and PhD degrees both in Electrical Engineering from INPG (Institute National Polytechniques Grenoble), France, in 2005 and 2009 respectively. Later on he served different organizations in France on several R&D positions. Currently he is working as an Assistant Professor in Effat University, KSA. (phone: +96-26364300; e-mail: sqaisar@effatuniversity.edu.sa).

The classical filtering techniques are time-invariant. They process the signal by employing a fixed order filter, which operates at a fixed sampling rate [1]. Due to this time-invariant nature they are parameterized for the worst case of the considered application. Thus, they are highly constrained especially in the case of low activity sporadic signals like electrocardiogram, phonocardiogram, seismic etc. It captures and processes a large number of redundant samples which increases the overall system activity and thus the power consumption [12, 14, 15].

This classical filtering shortcoming can be resolved up to a certain extent by employing the multirate filtering techniques [2, 21]. Following this multirate filtering approach, adaptive rate filtering techniques are devised. They are based on the Event Driven Sampling (EDS) [3]. The EDS adapts its sampling rate according to the input signal local variations [4-6]. Hence, it drastically reduces the post processing chain activity because it only samples the relevant information [6, 7]. Recently, the EDS has been employed in several fields of applications [3-16, 22, 23-25].

Section 2 briefly reviews the non-uniform signal processing tools employed in the proposed approach. A complete functionality of the proposed filtering technique is described in Section 3. Section 4 deduces the proposed technique computational complexity. Section 5 discusses the processing error. The proposed technique features are demonstrated with the help of an illustrative example in Section 6. In Section 7, the proposed technique performance is evaluated for a speech signal. Section 8 finally concludes the article.

II. NON-UNIFORM SIGNAL PROCESSING

The employed non-uniform signal processing tools are briefly described in the following subsections.

A. EDS (Event Driven Sampling)

The EDS is a natural choice for sampling a large variety of signals. Indeed, it lets the signal to pilot the sampling process [4]. The non-uniformity in the sampling process represents the signal local variations [5, 23]. In the case of EDS, a sample is captured only when the input analog signal x(t) crosses one of the predefined thresholds. Samples are not uniformly spaced in time because they depend on x(t) variations [6-8, 23].

According to [3], the sampling instants of a non-uniformly sampled signal obtained with the EDS are defined by Equation 1. Where, tn is the current sampling instant, tn-1 is the previous one and dtn is the time delay between the current and the previous sampling instants.

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

B. EDADC (EDS Based Analog to Digital Converter)

By employing the interesting EDS features, EDADCs have been developed. In [8-10], authors have shown advantages of EDADCs like the reduced activity, the power saving and the reduced electromagnetic emission. Inspiring from these interesting features, a EDADC is employed to digitize a band-limited analog signal x(t) in our studied case.

Classically, during an ideal A/D conversion process the sampling instants are exactly known, where as samples amplitudes are quantized at the ADC (A/D Converter) resolution [26], which is defined by the ADC number of bits. This error is characterized by the SNR (Signal to Noise Ratio) [26], which can be expressed by Equation 2 for a sinusoidal input.

$$SNR_{dB} = 1.76 + 6.02.M \,. \quad (2)$$

Here, M is the ADC number of bits. The SNR of an ideal ADC only depends on M and it can be improved by 6.02 dB for each increment in M.

The A/D conversion process, which occurs in EDADCs [8-10], is dual in nature. Ideally, the sample amplitudes are exactly known since they are equal to one of the predefined levels, while the sampling instants are quantized at the timer resolution T_{timer}. According to [8, 9], the SNR is given by Equation 3.

$$SNR_{dB} = -11.19 - 20\log\left(f_{sig}.T_{timer}\right). \quad (3)$$

f_{sig} is the sinusoidal frequency used for determining the SNR. It mainly shows that the SNR does not depend on M anymore, but on input signal characteristics and T_{timer}. An improvement of 6.02 dB in the SNR can be achieved by simply halving T_{timer}.

The choice of M is however crucial even for EDADCs. It should be taken large enough to ensure a proper signal reconstruction. This problem has been addressed in [24, 25]. In [24], it is shown that a band-limited signal can be ideally reconstructed from non-uniformly spaced samples if the average number of samples satisfies the Nyquist criterion. In the case of EDADCs, the average sampling frequency depends on M and the signal characteristics [8-10]. Thus, for a targeted application an appropriate M should be chosen in order to respect the reconstruction criterion [24].

C. ASA (Activity Selection Algorithm)

The EDADC delivers a non-uniform time repartitioned output. One drawback of EDADCs is that the relevant signal parts can be locally sampled at higher rates compared to the classical case [8, 13]. In the proposed approach this shortcoming is treated up to a certain extent by exploiting the level crossing sampled signal non-uniformity. It yields information on the signal local features. This information is employed to select only the relevant signal parts. Furthermore, characteristics of each selected part are analyzed and are employed later on to adapt the system parameters accordingly. This selection and local-features extraction process is called Activity Selection Algorithm [6, 11, 15].

The ASA displays interesting features with the EDADC, which are not available in the classical case. It selects only the active parts of the non-uniformly sampled signal, obtained with the EDADC. Moreover, it correlates the selected window length with the signal local characteristics. In addition, it provides an efficient reduction of the spectral leakage phenomenon [6, 15].

III. PROPOSED EVENT DRIVEN FILTERING

The proposed technique principle is show in Figure 1. The proposed technique is for the energy sensitive real time applications like biomedical implants, remote monitoring systems, distributed sensors, etc. The activity selection and the local features extraction are the proposed technique bases. They lead to the event driven sampling (only relevant samples to process) along with the event driven filtering (only relevant operations to deliver a filtered sample). It ensures a drastic computational gain of the proposed solution compared to the classical ones. The computation flow is detailed in the following subsections.

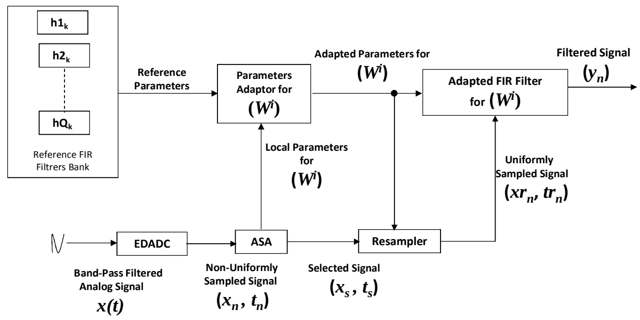


Fig. 1 Principal of the proposed filtering technique

A. Adaptive Rate Sampling

The EDADC sampling frequency is correlated to x(t) local variations [8, 14, 15]. For a given EDADC resolution M, the maximum and the minimum sampling frequencies are defined by Equations 4 and 5 respectively.

$$Fs_{\max} = 2.f_{\max}.\left(2^M - 1\right). \quad (4)$$

$$Fs_{\min} = 2.f_{\min}.\left(2^M - 1\right). \quad (5)$$

Here, f_{max} and f_{min} are the $x(t)$ highest and lowest frequencies. Fs_{max} and Fs_{min} are the EDADC maximum and minimum sampling frequencies respectively.

Let W^i represents the i^{th} selected window, obtained with the ASA [6, 14, 15]. The W^i length in seconds, L^i, can be computed as L^i=L^i+ dt_n. Here, dt_n is clear from Equation 1. The lower and upper bounds on L^i are respectively defined as $L^i \geq T_0$ and $L^i \leq Lmax$. Here, T_0 is the input signal, $x(t)$, fundamental period. $T_0 = 1/f_{min}$, f_{min} is clear from Equation 5. $Lmax$ is a function of system resources, maximum time frame which yields an upper bound on $Lmax$, used to process the incoming signal. If Fs^i is the EDADC sampling frequency for W^i, then it can be calculated by employing Equation 6. N^i is the number of samples laying in W^i.

$$Fs^i = \frac{N^i}{L^i} \cdot (6)$$

The upper and the lower bounds on Fs^i are posed by Fs_{max} and Fs_{min} respectively. In order to perform a classical filtering algorithm, the selected signal laying in W^i is uniformly resampled before the filtering stage (cf. Figure 1). Characteristics of the selected signal part laying in W^i are employed to choose its resampling frequency Frs^i. The resampling process changes the resampled signal properties compared to the original one. The resampling error depends on the employed interpolation technique. A procedure of choosing an appropriate interpolation technique for a targeted application and according to the employed system parameters is described in [15, 17, 19].

Once the resampling is done, there are Nr^i samples in W^i. Choice of Frs^i is crucial and this procedure is detailed in the following subsection.

B. Adaptive Rate Filtering

The proposed filtering approach is an enhancement of the techniques presented in [7, 12, 14]. It combines strengths of these previous approaches to achieve better performance.

The idea is to offline design a reference FIR filters bank for a targeted application. Here, offline refers to the non real time computation. The reference filters bank is designed with appropriate specifications for a set of reference sampling frequencies *Fref*. The upper bound on *Fref* is selected as F_r. F_r is a chosen frequency for the system, which satisfies the Nyquist sampling criterion. The process is clear from Equation 7.

$$F_r \geq F_{Nyq} = 2.f_{\max} . (7)$$

The choice of lower bound on *Fref* depends upon the filter transition band and the effective value of Fs_{min}. (cf. Equation 5). Let [Fc_{min}; Fc_{max}] defines the filter transition band. Now, if the condition: $Fs_{min} \geq 2.Fc_{max}$, becomes true then Fs_{min} is chosen as the lower bound on *Fref*. Otherwise, the lower *Fref* bound is chosen in such a way that it remains greater than or equal to $2.Fc_{max}$ [15].

Let us suppose that Fs_{min} defines the lower *Fref* bound. Then for a targeted application, an appropriate rule can be devised for distributing different *Fref* elements within the range [Fs_{min}; F_r]. In the considered case, they are placed uniformly. If Q is the length of *Fref*, then the process of computing the complete set is given by Equation 8. Δ is an offset. Its value can be calculated by using Equation 9.

$$Fref = \{Fs_{\min}, Fs_{\min}+\Delta, ..., Fs_{\min}+(Q-1)\Delta = F_r\}. (8)$$

$$\Delta = \frac{F_r - Fs_{\min}}{Q-1} . (9)$$

During the online computation, an appropriate reference filter is chosen for each W^i. Here, online refers to the real time. The reference filter choice is made on the base of *Fref* and the effective value of Fs^i. If $Fs^i \geq F_r$, then the reference filter which is offline designed for F_r is employed for W^i. Otherwise, if $Fs^i < F_r$, then the reference filter whose corresponding value of $Fref_c$ is closest and greater or equal to Fs^i is chosen for W^i. Here, c is the index notation which makes a distinction between the chosen reference frequency and the frequencies available in the reference filter bank.

Later on $Fref_c$ and Fs^i are used to define Frs^i and a decimation factor d^i. Frs^i is employed to uniformly resample the selected signal laying in W^i, where d^i is employed to decimate hc_k for W^i. Here, hc_k represents the coefficients of chosen reference filter for W^i.The choice of Frs^i depends on $Fref_c$ and Fs^i. For proper filtering operation Frs^i should match to $Fref_c$. The techniques for selecting Frs^i and keeping it coherent with $Fref_c$ are detailed as follow.

In the first case, when $Fs^i \geq F_r$, $Frs^i = F_r$ is chosen and hc_k remains unchanged. This choice of Frs^i makes to resample W^i closer to the Nyquist rate, so avoids unnecessary interpolations during the data resampling process. It improves the processing efficiency.

In the second case, $F_r > Fref_c = Fs^i$ holds. Here, $Frs^i = Fref_c$ is chosen and hc_k again remains unchanged.

In the third case, $F_r > Fref_c > Fs^i$ holds. Here, $Frs^i = Fs^i$ is chosen and hc_k is online decimated in order to reduce $Fref_c$ to Frs^i. In this case, the chosen reference filter order is reduced for W^i, which reduces the number of operations to deliver a filtered sample. Hence, it further improves the proposed techniques computational efficiency. In this case, it appears that Frs^i may be lower than the Nyquist frequency of $x(t)$ and so it can cause aliasing. According to [8, 13], an appropriate choice of the EDADC dynamic range ΔV_{in} and the resolution M can be made by exploiting the signal statistics. It ensures that the signal will cross enough consecutive thresholds. Thus, it is locally oversampled with respect to its local bandwidth and so the risk aliasing is canceled.

In order to decimate hc_k, the decimation factor d^i for W^i is online computed by employing Equation 10.

$$d^i = \frac{Fref_c}{Frs^i} . (10)$$

d^i can be specific for each selected window depending on Frs^i and $Fref_c$. $D^i = floor(d^i)$ is computed, in order to determine whether d^i is integral or float. *If* ($D^i = d^i$) holds, then hc_k is decimated with D^i to deliver h^i_j (see Equation 11). j is indexing the decimated filter coefficients. If the order of hc_k is P_c, then the order of h_j^i is given as: $P^i = P_c / D^i$.

$$h^i_j = hc_{D^i.k} . (11)$$

A simple decimation causes a reduction of the decimated filter energy compared to the reference. It leads to an attenuated filtered signal. D^i is a good approximate of the ratio between the reference filter energy and that of the decimated one. Therefore this decimation is compensated by scaling h_j^i with D^i. The process is clear from Equation 12.

$$h^i_j = D^i.hc_{D^i.k} . (12)$$

For a fractional d^i, Frs^i is given by: $Frs^i = Fref_c / d^i$, so it remains equal to Fs^i. For the fractional d^i the process for matching $Fref_c$ with Frs^i is achieved by resampling hc_k at Frs^i. The effect of online hc_k decimation is compensated by scaling the decimated filter coefficients, h_j^i, with d^i. The complete procedure of calculating Frs^i and h_j^i for the EARR technique is described on Figure 2.

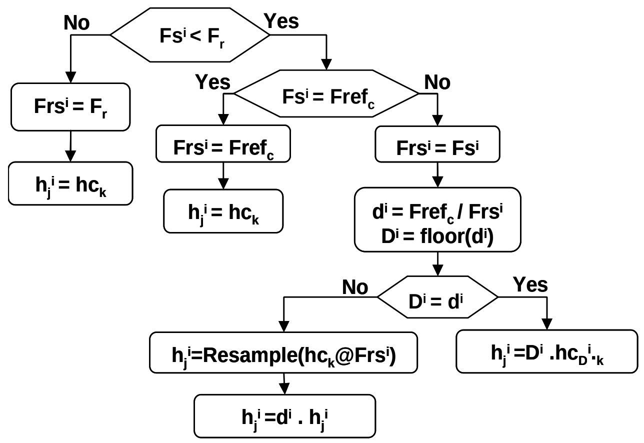


Fig. 2 The proposed technique flowchart

IV. THE COMPUTATIONAL COMPLEXITY

It is well known that a classical P order FIR filter performs P additions and P multiplications to deliver each filtered sample [1]. If N is the number of samples then the total computational complexity C can be calculated by employing Equation 13.

$$C = \underbrace{P.N}_{Additions} + \underbrace{P.N}_{Multiplications} \quad (13)$$

In the proposed technique, the adaptation process requires extra operations for each selected window. The proposed technique complexity C_{ED} is computed in the sequel. The first step is the choice of a reference filter hc_k for W^i. In the worst case, it requires Q comparisons. Here, Q is the number of reference frequencies in the *Fref set*. The filtering case selection requires two comparisons (cf. Figure 3). The data resampling operation is performed by employing the NNRI (Nearest Neighbour Resampling Interpolation). The NNRI is chosen because of its simplicity. Indeed it uses only one non-uniform sample for each resampled sample. Moreover, it provides an unbiased approximation of the original signal variance [17]. The NNRI is performed as follow.

For each interpolation instant tr_n, the interval of non-uniform samples $[t_n, t_{n+1}]$, within which tr_n lays is determined. Then the distance of tr_n to each t_n and t_{n+1} is computed and a comparison among the computed distances is performed to decide the smaller among them. For W^i, the complexity of the first step is N^i+Nr^i comparisons and the complexity of the second step is $2Nr^i$ additions and Nr^i comparisons. Hence, the NNRI total computational complexity for W^i becomes N^i+2Nr^i comparisons and $2Nr^i$ additions.

In the case, when $Fs^i<Fref_c$, the decimation of hc_k is required. In this goal, d^i is computed by performing a division between $Fref_c$ and Frs^i. D^i is calculated by employing a floor operation on d^i. A comparison is made between D^i and d^i. When $D^i=d^i$, the process of obtaining h_j^i is simple. The decimator simply picks every $(D^i)^{th}$ coefficient from hc_k. It has a negligible complexity compared to operations like addition and multiplication. This is the reason why this cost is not taken into account for the complexity evaluation process. Later on the decimated filter impulse response is scaled, it requires P^i multiplications. Here, P^i is the h_j^i order.

In the case of fractional d^i, a fractional decimation of hc_k is achieved. It is done by resampling hc_k at Frs^i. The resampling is performed with the NNRI, which performs $P+2P^i$ comparisons and $2P^i$ additions to deliver h_j^i. (cf. Figure 2). Finally, a P^i order filter performs $P^i.Nr^i$ multiplications and $P^i.Nr^i$ additions for W^i. The computational complexity of the proposed technique C_{EDR} is given by Equation 14.

$$C_{EDR} = \sum_{i=1}^{I} \underbrace{\alpha}_{Divisions} + \underbrace{\alpha}_{Floor} + \underbrace{Nr^i\left(P^i+2\right)+2\alpha\beta P^i}_{Additions} + \underbrace{P^i\left(Nr^i+\alpha\right)}_{Multiplications} + \underbrace{N^i+2Nr^i+Q+2+\alpha\left[1+\beta\left(P_c+2P^i\right)\right]}_{Comparisons} \quad (14)$$

where:

- i represents the selected windows index.
- α is 1 when $F_r>Fs^i<Fref_c$ and 0 otherwise.
- β is 0 when $d^i=D^i$ and 1 otherwise.

V. FILTERING ERROR

In the proposed filtering technique, hc_k is employed to filter W^i. Depending on the chosen Frs^i, it can be required to online decimate hc_k. This online decimation can cause a filtering precision degradation [7, 12, 14, 15]. In order to evaluate this phenomenon, the following procedure is adopted to estimate the filtering error.

First a reference filtered signal is generated. Then instead of decimating hc_k to obtain h_j^i, a specific filter h^i_m is designed for W^i by using the Parks-McClellan algorithm. It is designed for Frs^i by employing the same hc_k design parameters. The signal part corresponding to W^i is sampled at Frs^i with a high precision uniform ADC. This sampled signal is filtered by employing h^i_m. The filtered signal obtained in this way is used as the reference for W^i and its comparison is made with the results provided by the proposed techniques.

Let y_n is the n^{th} reference filtered sample and $\hat{y}_n$ is the n^{th} filtered sample obtained with the proposed filtering technique. Then, the mean filtering error for W^i can be calculated by employing Equation 15.

$$MFE^i = \frac{1}{Nr^i}\sum_{n=1}^{Nr^i}\left|y_n - \hat{y}_n\right|. \quad (15)$$

VI. ILLUSTRATIVE EXAMPLE

In order to illustrate the interesting features of the proposed techniques, an input signal *x(t)* shown on the left part of Figure 3 is employed. Its total duration is 20 seconds and it consists of three active parts. Summary of *x(t)* activities is given in Table 1.

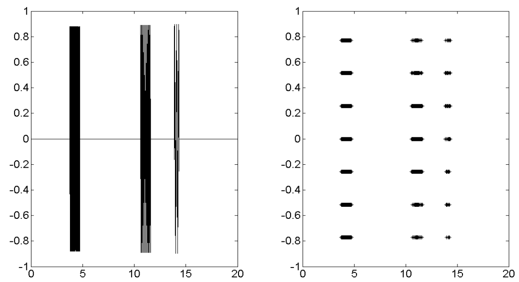


Fig. 3 The input signal (left) and the selected signal (right)

Activity	*Signal Components*	Length (Sec)
1st	0.5sin(2π20t)+ 0.4sin(2π1000t)	0.5
2nd	0.45sin(2π25t)+ 0.45sin(2π150t)	1.0
3rd	0.6sin(2π15t)+ 0.3sin(2π100t)	1.0

TABLE 1: SUMMARY OF THE INPUT SIGNAL ACTIVE PARTS

Table 1 shows that *x(t)* is band limited between f_{min}=15Hz and f_{max}=1kHz. In this case, *x(t)* is digitized by employing a 3-bit resolution EDADC. Thus, the corresponding minimum and maximum sampling frequencies are Fs_{min}=210Hz and Fs_{max}=14kHz. The EDADC amplitude range ΔV_{in}=1.8V is chosen. Each activity window contains a low and a high frequency component (cf. Table 1). In order to filter the high frequency part from each window, a bank of 11 low-pass reference FIR filter is implemented by employing the standard Parks-McClellan algorithm. F_r=2500Hz is chosen thus Δ=229 Hz becomes in this case (cf. Equation 9). The reference filters are designed for the same design parameters except for the reference sampling frequency. The cut-off frequency and the transition band are respectively chosen as 30Hz and [30; 80]Hz. The Pass-band and the stop-band ripples are chosen at -25dB and -80dB respectively. The obtained values of $Fref_c$ and P_c for each reference filter hc_k are given in Table 2.

The non-uniformly sampled signal obtained at the EDADC output is selected and windowed by the ASA. In order to apply the ASA, the reference window length L_{ref} is chosen equal to 1 second. The ASA delivers three selected windows for the whole *x(t)* span of 20 seconds, which are shown on the right part of Figure 3. The selected windows parameters are displayed by Table 3.

In this case, a reference filter is chosen for each selected window (cf. Section 3). The chosen values of $Fref_c$ and the calculated values of Frs^i, d^i, Nr^i and P^i for the proposed technique are summarized in Table 4. The procedure of calculating these values is clear from Figure 2.

hc_k	$h1_k$	$h2_k$	$h3_k$	$h4_k$	$h5_k$	$h6_k$
$Fref_c$ (Hz)	210	439	668	897	1126	1355
P_c	8	21	33	45	57	69
hc_k	$h7_k$	$h8_k$	$h9_k$	$h10_k$	$h11_k$	
$Fref_c$ (Hz)	1584	1813	2042	2271	2500	
P_c	80	92	104	115	127	

TABLE 2: SUMMARY OF THE REFERENCE FILTERS BANK PARAMETERS

W^i	L^i (Sec.)	N^i (Samples)	Fs^i (HZ)
1st	0.49	3000	6000
2nd	0.99	1083	1083
3rd	0.99	464	464

TABLE 3: SUMMARY OF THE SELECTED WINDOWS PARAMETERS

W^i	Fs^i (Hz)	$Fref_c$ (Hz)	Frs^i (Hz)	Nr^i (Samples)	D^i	P^i
1st	6000	2500	2500	1250	1.0	127
2nd	1083	1126	1126	1126	1.0	57
3rd	464	668	668	668	1.0	33

TABLE 4: PARAMETERS SUMMARY FOR THE PROPOSED TECHNIQUE

Tables 3-4 jointly exhibit the proposed technique interesting features, which are achieved by an intelligent combination of the non-uniform sampling scheme and the uniform signal processing tools (cf. Figure 1). Fs^i represents the sampling frequency adaptation by following the local variations of *x(t)*. N^i shows that the relevant signal parts are locally over-sampled in time with respect to their local bandwidths [7, 12]. Frs^i shows the adaption of the resampling frequency for each selected window. It further adds to the proposed techniques computational gain by avoiding the unnecessary interpolations during the resampling process. Nr^i shows how the adjustment of Frs^i avoids the processing of unnecessary samples during the post filtering process. P^i represents how the adaptation of h_k for W^i avoids the unnecessary operations to deliver the filtered signal. L^i exhibits the dynamic feature of ASA, which is to correlate to L_{ref} with the signal activity laying in it [6, 14].

These results have to be compared with classical case. If F_{ref} is chosen as the sampling frequency, then the total *x(t)* span is sampled at 2500 Hz. It renders N=20×2500=50000 samples to process with the 127th order FIR filter. However, in the proposed technique the total number of resampled data points is much lower and it is 3044. Moreover, the local filters orders for W^2 and W^3 are also lower than 127. It promises the computational efficiency of the proposed technique compared to the classical one. A detailed complexity comparison is made in the following subsection.

A. Complexity Comparison with the Classical Approach

From Section 4, it is clear that the proposed technique performs operations like comparisons, divisions and floors which differ from the classical one. In order to make the techniques comparable, it is assumed that a comparison has the same processing cost as an addition and a division or a floor has the same processing cost as a multiplication. With these assumptions, the complexities of the proposed technique C_{ED} is given by Equation 16.

$$C_{EDR} = \sum_{i=1}^{I} \underbrace{N^i + Nr^i\left(P^i + 4\right) + \alpha\left[1 + \beta\left(P_C + 4P^i\right)\right] + 2 + Q}_{Additions} + \underbrace{P^i Nr^i + \alpha\left(P^i + 2\right)}_{Multiplications} \quad \text{. (16)}$$

The proposed technique computational gain over the classical one is computed by employing results, summarized in Tables 3-4. These results are computed with different x(t) time spans and are summarized in Table 5.

Time Span (Sec.)	L^1	L^2	L^3
Gain in Additions	1. 9	5.4	27.5
Gain in Multiplications	2.0	5.8	30.5

Table 5: Computational Gain of the Proposed Technique over the Classical Filtering

The gain in additions and multiplications of the proposed technique is clear from Table 5. For W^1, where the resampling frequency and the filter order is identical as the classical case (cf. Table 4), the gain is achieved thanks to the proposed adaptive technique. This is only due to the fact that the ASA correlates the window length to the activity (0.5 second), while the classic case computes during the total duration of T_{ref} =1 second. The gains are of course much larger in the other windows, since the proposed techniques benefit of processing less samples with lower filter orders. For the whole span of *x(t)* (20 seconds), the proposed technique also takes advantage of the idle parts of *x(t)*, which further induces additional gains compared to the classical case.

These results confirm that the proposed filtering achieves a drastic reduction in the number of operations. This reduction in operations is obtained by employing the joint benefits of the EDADC, the ASA and the resampling. Indeed, they enable to adapt simultaneously the sampling frequency and the filter order by following the input signal local variations.

B. Filtering Error

The online adjustment of hc_k leads to a drastic computational gain of the proposed technique compared to the classical one (cf. Section 6.1). However, it can render a reduced filtering quality compared to the classical case. The issue is addressed in this section.

The mean filtering error (MFE) of the proposed technique is calculated, for each activity window by employing Equation 15. The obtained results are summarized in Table 6.

Table 6 shows that the online decimation of hc_k in the proposed technique causes a loss of the filtering quality. Indeed, the filtering error increases with d^i. The measure of this error can be used to fix an upper bound on d^i (by performing an offline calculation), for which the decimated and the scaled filters provide results with an acceptable level of accuracy. Moreover, for the high precision applications, an appropriate filter can be online calculated for each selected window at the cost of an increased computational load. To conclude, an accuracy enhancement is achievable at the cost of a reduction of the processing efficiency.

Selected Window	W^1	W^2	W^3
MFE^i	-36.2	-31.4	-27.4

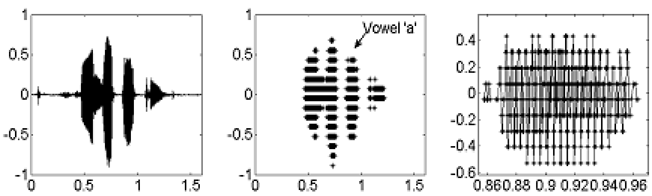
Table 6: Mean Filtering Error of Each Selected Window

VII. CASE STUDY

In order to evaluate the proposed technique performances for real signals, a speech signal *x(t)* shown on Figure 4-a is employed. *x(t)* is a 1.6 second, [50Hz; 4000Hz] band-limited signal. The goal is to determine the pitch (fundamental frequency) of *x(t)* in order to determine the speaker's gender. For a male speaker, the pitch lays within the frequency range [100Hz, 150Hz], whereas for a female speaker, the pitch lays within the frequency range [200Hz, 300Hz] [22]. F_r=16kHz is chosen, which is a common sampling frequency for speech. A 4-bit resolution EDADC is used for digitizing *x(t)* and we have Fs_{min}=1.5kHz and Fs_{max}=120kHz. The EDADC amplitude range is always set to ΔV_{in}=1.8V. It renders into the quantum $q=\Delta V_{in}/(2^M-1)$=0.12V (for M=4). The amplitude of *x(t)* is normalized to 0.9V in order to avoid the EDADC saturation.

The studied signal is part of a conversation. During a dialog, the speech activity is about 25% of the total time span [18]. A classical filtering system would remain active during the 100% dialog duration. However, the proposed filtering techniques will remain active only during 25% of the dialog time span, which will reduce the system power consumption.

A speech signal mainly consists of vowels and consonants. Consonants are of lower amplitude compared to vowels [18]. In order to determine the speakers pitch, vowels are the relevant *x(t)* parts. For *q*=0.12V, consonants are ignored during the signal acquisition process and are considered as low amplitude noise. In contrast, vowels are locally over sampled like any harmonic signal [7, 12, 15]. This intelligent signal acquisition further avoids the processing of useless samples, within the 25% of *x(t)* activity and so further improves the proposed techniques computational efficiency.



4-a 4-b 4-c

Fig. 4 The input signal (4-a), the selected signal (4-b) and the zoom of the second window (4-c)

Although the consonants are partially filtered out during the data acquisition process, yet for proper pitch estimation, it is required to filter out the remaining effect of high frequencies, still present in *x(t)*. To this aim, a bank of reference low pass filters is designed, with the standard Parks-McClellan algorithm. F_r=16kHz is chosen thus Δ=1450Hz (cf. Equation 9). The Cut-off frequency is chosen equal to 300Hz. The transition band is chosen between [300; 4000]Hz. The pass-band and stop-band ripples are chosen as -25dB and -80dB respectively. The corresponding values of $Fref_c$ and P_c for each reference filter hc_k are given in Table 7.

hc_k	$h1_k$	$h2_k$	$h3_k$	$h4_k$	$h5_k$	$h6_k$
$Fref_c$ (Hz)	1500	2950	4400	5850	7300	8750
P_c	38	75	112	148	185	222
hc_k	$h7_k$	$h8_k$	$h9_k$	$h10_k$	$h11_k$	
$Fref_c$ (Hz)	10200	11650	13100	14550	16000	
P_c	258	295	332	368	405	

Table 7: Summary of the Reference Filters Bank Parameters

In order to apply the ASA, L_{ref} =0.5 seconds is chosen. The ASA delivers three selected windows, which are shown on Figure 4-b. The parameters of each selected window are summarized in Table 8.

W^i	L^i (Sec.)	N^i (Samples)	Fs^i (Hz)
1st	0.207	2360	11379
2nd	0.114	347	3054
3rd	0.121	265	2190

Table 8: Summary of the Selected Windows Parameters

To find the pitch, we now focus on W^2 which corresponds to the vowel 'a'. A zoom on this signal part is plotted on Figure 4-c. The chosen values of $Fref_c$ and the calculated values of Frs^2, d^2, Nr^2 and P^2 for the proposed technique are summarized in Table 9. The procedure of calculating these values is depicted in Section 3.

Selected Window	$Fref_2$ (Hz)	Frs^2 (Hz)	Nr^2 (Samples)	d^2	P^2
W^2	4400	3054	347	1.4	77

Table 9: The Proposed Technique Parameters for the Second Selected Window

In order to make a performance comparison between the proposed technique and the classical one, the sampling frequency and the window function length are chosen equal to F_r and L_{ref} in the classical case. The computational gain of the proposed approach compare to the classical one is computed by employing Equations 13 and 16. The obtained results for W^2 are summarized in Table 10.

Table 10 confirms the proposed technique computational efficiency compared to the classical approach. It is gained firstly, by achieving the smart signal acquisition and secondly, by adapting the sampling frequency and the filter order according to the local variations of *x(t)*. When considering a complete dialogue, the proposed technique will also take advantage of the idle *x(t)* parts (75%), which will further induce additional gains compared to the classical approach.

Selected Window	Gain in Additions	Gain in Multiplications
W^2	16.17	16.26

Table 10: Summary of the Computational Gain for the Second Selected Window

For the proposed technique, an online decimation of the chosen reference filter can be required. Thus a risk of reducing the reference filter accuracy occurs for this approach (cf. Section 6). A quality comparison is made between the reference filtering and the proposed one. In this aim, the magnitude responses of the reference and the proposed approach filter for the W^2 are plotted respectively on Figures 5 and 6. Moreover, the spectra of the filtered signal laying in W^2, obtained with the reference filter and the proposed one are plotted respectively on Figures 7-a and 7-b. The zoom of first spectral peaks on Figures 7-a and 7-b are presented respectively on Figures 8-a and 8-b.

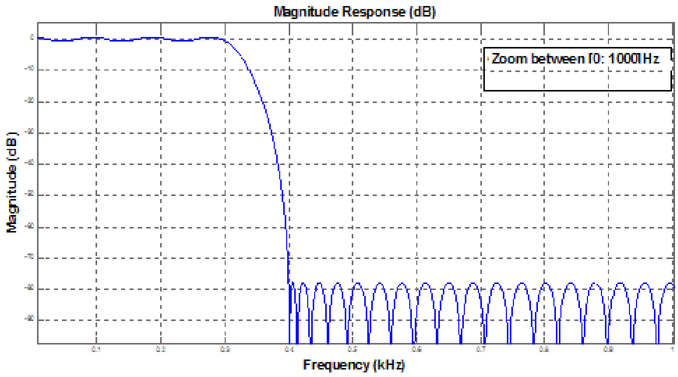


Fig. 5 Magnitude response of the filter, classical approach

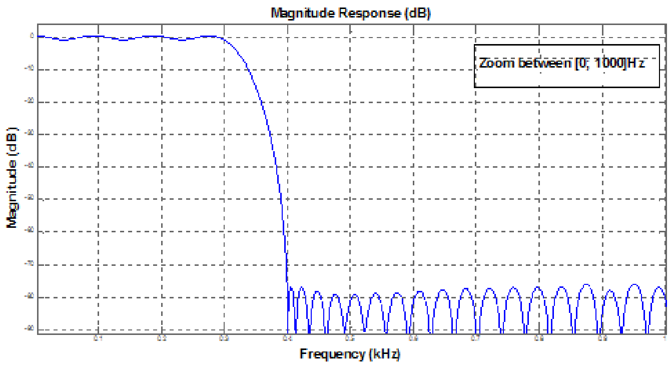
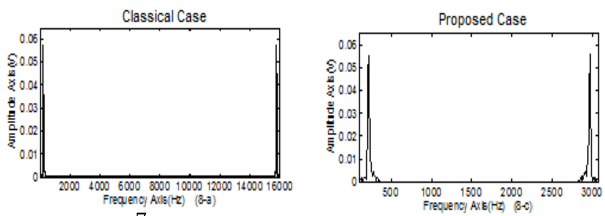


Fig. 6: Magnitude response of the filter, proposed approach



7-a 7-b

Fig. 7 Spectra of the filtered signal obtained with the classical approach (7-a) and with the proposed approach (7-b)

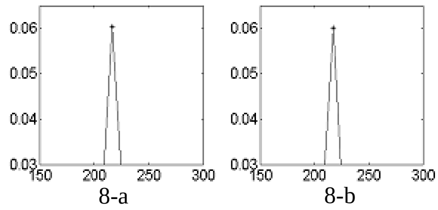


Fig. 8 Zoom of spectra of the filtered signal obtained with the classical approach (8-a) and with the proposed approach (8-b)

The spectra on Figure 8 show that the fundamental frequency is about 215 HZ. Thus, we can easily conclude that the analyzed sentence is pronounced by a female speaker. Although it is required to online decimate the reference filter for the proposed approach the filter response and the spectra of the filtered signal obtained with this technique are quite comparable to results obtained with the reference filtered signal. It shows that, for the chosen parameters, the results are of acceptable quality for the targeted application.

VIII. CONCLUSION

A novel event driven filtering technique has been devised. For the proposed technique, a reference filters bank is offline computed by taking into account the input signal statistical characteristics and the application requirements. A complete procedure of obtaining the resampling frequency Frs^i and the decimated filter coefficients h_j^i for W^i is described for the proposed technique.

The proposed technique computational complexity is deduced and compared with the classical one. It is shown that the proposed technique results into a drastic gain in terms of the computational load. This is achieved by employing benefits of the EDADC, the ASA and the resampling process as they allow an online adaptation of parameters (Fs^i, Frs^i, N^i, Nr^i, d^i and P^i) by exploiting the input signal local variations. It drastically reduces the total number of operations and the power consumption.

A method to compute the filtering error is also devised. It is shown that error made by the proposed technique is minor for the studied case. A higher precision can be achieved by increasing the EDADC resolution or the interpolation order. Thus, a suitable solution can be proposed for a targeted application by making an appropriate tradeoff between the accuracy level and the computational load.

Speech is a common and easily accessible signal. Therefore at first time the proposed technique performance has been studied for a speech application. The devised approach versatility lays in the appropriate choice of system parameters like the EDADC resolution M, the distribution of level crossing thresholds, the interpolation order, etc. These parameters should be tactfully chosen for a targeted application, so that they ensure an attractive tradeoff between the system computational complexity and the delivered output quality.

The proposed technique circuit level implementation is in progress. A detailed study of the proposed filtering technique computational load by taking into account the circuit level processing cost is a potential task. Future works focus on the proposed technique optimization and its employment to other potential applications.

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Dr. Saeed Mian Qaisar has received his Masters and PhD degrees both in Electrical Engineering from INPG (Institute National Polytechniques Grenoble), France, in 2005 and 2009 respectively. Later on he served different organizations in France on several R&D positions. Currently he is working as a consultant. His areas of interest are Sampling Theory, Intelligent Systems, SoC (System on Chip), Adaptive Filtering, Real Time and Multi Rate Processing and Multi Resolution Analysis.