

SUB-BAND ADAPTIVE SPEECH ENHANCEMENT USING CRITICAL SAMPLING AND EIGEN VALUE SPREAD

***D. Prapulla Kumar¹ and I. Santi Prabha²**

¹Department of ECE, JNTU University, Kakinada, AP, India

²Department of ECE, JNTU University, Kakinada, AP, India

**Author for Correspondence*

ABSTRACT

Now a days Speech processing methods are usually implemented in the time frequency domain. Filter bank can be considered as a divide and conquer approach within signal processing, since large problems are sub-divided into many smaller problems. While filter banks are essential components of speech processing, and in signal processing in general, they will have the focus on present days. An adaptive filter is a filter that self adjusts its transfer function according to its optimizing algorithms, adaptive filters are digital filters they perform digital signal processing. Least mean square algorithm has slow convergence when used in ill conditioned input such as speech but it has high computational cost. To improve the convergence rate and computational complexity and also to overcome the disadvantage of a full band adaptive filtering, we proposed a new structure that is sub band adaptive filtering; this will converge faster at a lower computational cost for speech and white noise input. The analysis is done using MATLAB.

Key Words: *Inter Band Aliasing, Adaptive Filtering, Sub Band Adaptive Filtering*

INTRODUCTION

Adaptive filters are attractive in many applications as they exhibit a number of desirable properties such as stability and uni-modal performance surface. However, major drawbacks are the large number of operations needed for their Implementation and slow convergence when the length of the FIR filter is very large. Alternative structures that make use of filter bank concepts have been proposed with the objective of reducing the drawbacks described above. One important method that improves the performance and reduces the computational cost is sub band adaptive filtering (SAF), in which input signal is divided into a number of sub band signals and the adaptive filtering is performed on each sub band. It has the potential for a faster convergence and a lower computational complexity than a full band structure. It mainly suffers from two deficiencies. First, inter band aliasing that is introduced by down sampling process required in reducing the data rate is unavoidable that degrades the performance. Second, the filter bank introduces additional computation and system delay. For this a newly proposed structure is introduced that is free alias SAF structure. In each sub band, the inter band aliasing is obtained using a bandwidth-increased linear-phase FIR analysis filter, whose pass band has almost-unit, magnitude response in the sub band interval, and is then subtracted from the sub band signal. This aliasing cancelation procedure causes the spectral dips of the sub band signals. These spectral dips can be reduced by using a simple FIR filter.

SYSTEM MODEL

Figure show that the block diagram of sub band adaptive filtering. This is also called as synthesis independent structure.

The full band input signal $u(n)$ and desired response $d(n)$ are decomposed into N spectral bands using analysis filters. $H_i(z)$, $i = 0, 1, \dots, N-1$. These sub band signals are decimated to a lower rate using the same factor D and are processed by individual adaptive sub filters $W_i(Z)$. Each sub filter has an independent adaption loop with computed error signal $E_{i,D}(Z)$ for updating the tap weights to minimize the corresponding sub-band error signal. At last the obtained error signals can be interpolating combining all the signals using a synthesis filter bank.

The reconstructed output of a sub band adaptive structure has small errors because of slow convergence rate. To resolve this problem we design analysis and synthesis filters as follows the analysis filter is

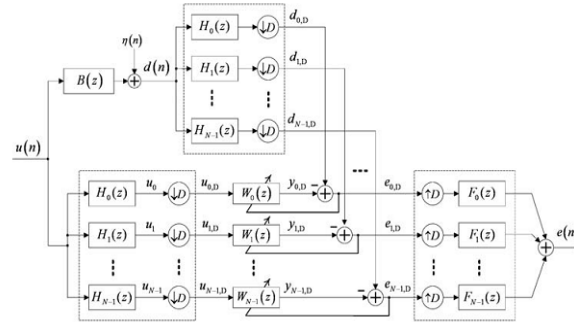


Figure 1: sub band adaptive filter structure

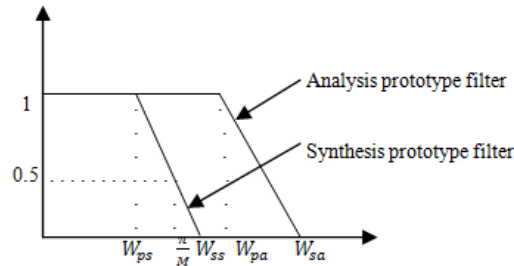


Figure 2: A possible choice of analysis and synthesis prototype filters which resolves the problem of slow convergence of sub band adaptive filters.

chosen such that it has a flat magnitude response and linear phase response (constant group delay) between zero and a frequency larger than or equal to W_{ss} , where W_{ss} is the beginning of the stop band of the synthesis prototype filter can be shown in above figure.

The primary motivations of using SAF are to reduce the computational complexity and improve the convergence performance for the input signal with a large spectral dynamic range, i.e. the input signal is highly correlated adaptive sub filters. Consider an application where the unknown system $B(z)$ is modeled by a full band adaptive filter $W(z)$ of length M . Since the sub filters $W_i(z)$ operate at a lower rate with the decimation factor D , the length of the adaptive sub-filters can be reduced to $L = M/D$.

There are a total of $L \times N = MN/D$ sub band tap weights for N sub bands. Thus the number of multiplications required by N sub-filters is MN/D^2 . Compared with the full-band filtering that requires M multiplications, the computational saving in terms of multiplications can be expressed as

$$\frac{\text{complexity of full band filter}}{\text{complexity of sub filter}} = \frac{D^2}{N}$$

Where $D=N$ is used for a critically sampled SAF to achieve the greatest computational savings and $D<N$ for an oversampled SAF to minimize the aliasing distortion.

SUB BAND ADAPTIVE FILTERING WITH CRITICAL SAMPLING

In SAF structure signals are decomposed into a number of sub band signals using an analysis filter bank, and adaptive filtering is performed on each sub band. These gradient-based algorithms suffer from slow convergence when the input signal is highly correlated. This problem is related to the large Eigen value spread in the input autocorrelation matrix due to the large spectral dynamic range of the input signal. Sub

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band decomposition followed by a critical decimation ($D = N$) reduces the spectral dynamic range in each sub band, i.e. faster convergence can be achieved because the spectral dynamic range of the sub-band signal is smaller than that of the full-band signal.

The sub-band error signal $e_{i,D}(n)$ is the difference between the filter output $y_{i,D}(n)$ and the desired response $d_{i,D}(n)$ expressed as

$$e_{i,D}(k) = d_{i,D}(k) - W^T(k) u_i(k) \text{ for } i = 0, 1, \dots, N-1.$$

The error signal vector for D sub bands,

$$e_D(k) = [e_{0,D}(k), e_{1,D}(k), e_{2,D}(k), \dots, e_{N-1,D}(k)]^T \text{ can be expressed as, } e_D(k) = d_D(k) - U^T(k)w(k)$$

A critically sampled SAF with D sub bands, the K th sub-band error $E_k(Z)$.

$$E_k(Z) = \frac{1}{D} \sum_{i=0}^{D-1} H_k \left(Z^{\frac{1}{D}} G_D^i \right) H \left(Z^{\frac{1}{D}} w_D^i \right) \times U \left(Z^{\frac{1}{D}} G_D^i \right) - \frac{1}{D} W_k(Z) \times \sum_{i=0}^{D-1} H_k \left(Z^{\frac{1}{D}} w_D^i \right) U \left(Z^{\frac{1}{D}} w_D^i \right)$$

Where $U_k(Z), W_k(Z), E_k(Z), H_k(Z)$ are representation of z transforms of input signal unknown signal, k th analysis filter and the k th synthesis filter. For $k=0, 1, 2, \dots, D-1$. Where $w_D^i = e^{-\frac{j2\pi i}{D}}$ and then analysis filter is a band pass filter, whose pass band is $k\pi/D \leq \omega \leq (k+1)\pi/D$.

$$M.E_k(Z) = H \left(Z^{\frac{1}{D}} \right) - W_k(Z) \left[H_k \left(Z^{\frac{1}{D}} X \left(Z^{\frac{1}{D}} \right) + [H \left(Z^{\frac{1}{D}} w_D^k \right) - W_k(Z)] \times H_k \left(Z^{\frac{1}{D}} w_D^k \right) X \left(Z^{\frac{1}{D}} w_D^k \right) + [H \left(Z^{\frac{1}{D}} w_D^{k+1} \right) - W_k(Z)] \times H_k \left(Z^{\frac{1}{D}} w_D^{k+1} \right) X \left(Z^{\frac{1}{D}} w_D^{k+1} \right) + \varepsilon_k(Z) \right]$$

$$\text{Where } \varepsilon_k(Z) = \frac{1}{D} \sum_{i=1}^{D-1} H_k \left(Z^{\frac{1}{D}} G_D^i \right) H \left(Z^{\frac{1}{D}} w_D^i \right) \times U \left(Z^{\frac{1}{D}} G_D^i \right) - \frac{1}{D} W_k(Z) \times \sum_{i=1}^{D-1} H_k \left(Z^{\frac{1}{D}} w_D^i \right) U \left(Z^{\frac{1}{D}} w_D^i \right)$$

When the filter bank is a real-valued, the terms $H_k \left(Z^{\frac{1}{D}} w_D^k \right)$ and $H_k \left(Z^{\frac{1}{D}} w_D^{k+1} \right)$ are adjacent to $H_k \left(Z^{\frac{1}{D}} \right)$ as shown by their magnitude responses in Fig. 3

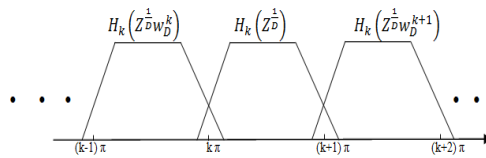


Figure 3: Magnitude response of $H_k \left(Z^{\frac{1}{D}} \right)$ and its adjacent terms $H_k \left(Z^{\frac{1}{D}} w_D^k \right)$ and $H_k \left(Z^{\frac{1}{D}} w_D^{k+1} \right)$.

In fig 3 the errors introduced by inter-band aliasing due to the overlapping between $H_k \left(Z^{\frac{1}{D}} w_D^k \right)$ and $H_k \left(Z^{\frac{1}{D}} \right)$, also between $H_k \left(Z^{\frac{1}{D}} w_D^{k+1} \right)$ and $H_k \left(Z^{\frac{1}{D}} \right)$. To reduce the value of $\varepsilon_k(Z)$ to a value close to zero, the adaptive filter has to match the two different frequency responses.

DELAY LESS-ALIAS FREE SUB BAND ADAPTIVE FILTERING WITH CRITICAL SAMPLING

The down sampling process is essential in almost all multi rate signal processing for making the overall data rate nearly equivalent to that of the input. Due to down sampling inter band aliasing is occurred. The inter band aliasing is a major bottleneck in using SAF. It is proposed critically sampled SAF that is almost

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alias free. The inter band aliasing is extracted in each sub band using the bandwidth-increased FIR linear-phase analysis filters and then subtracted from each sub band signal. The resultant alias-free sub band signals have spectral dips, so the spectral dips are reduced using a filter for the spectral flatness and then the outputs are used for adaptive filtering in each sub band.

Fig. 4 shows the magnitude responses $U_k(e^{j\omega})$ of the signal that has passed through the k th analysis filter, whose transition band width is $\frac{\omega\delta}{D}$

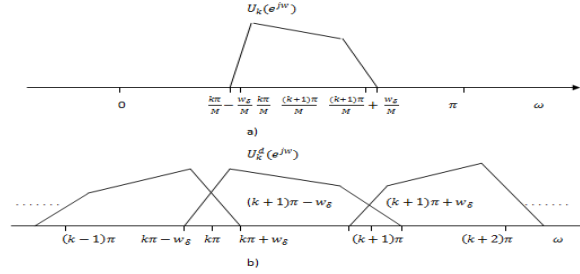


Figure 4: Magnitude responses of the k th sub band a) output of the k th analysis filter b) and it's down sampled version.

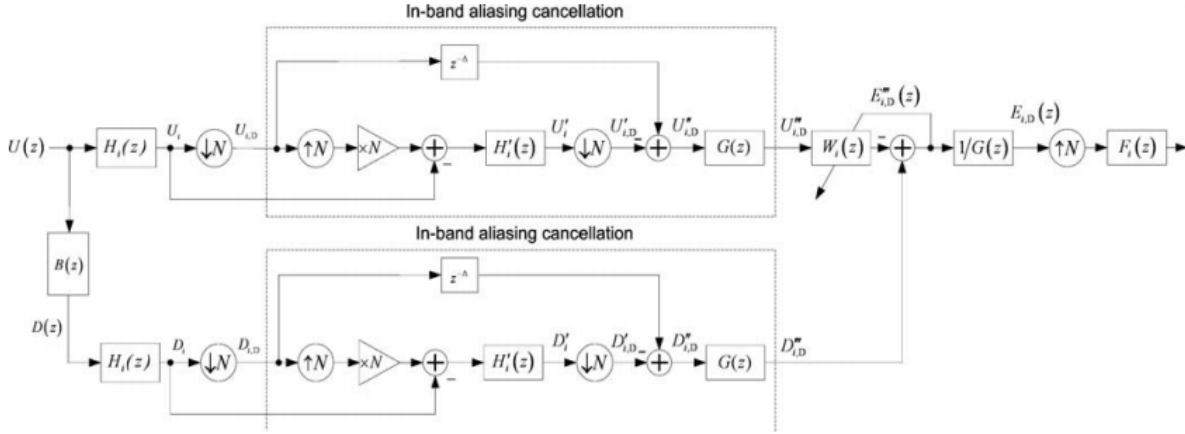


Figure 5: Block diagram of the alias free sub band adaptive filtering with critical sampling in the k th sub band

A linear-phase band width-increased analysis filter $H_i(e^{j\omega})$ of order $2KN$, where K is an integer, was recently proposed for the cancellation of in-band aliasing.

The output of filter $U_i(e^{j\omega})$ consists of inter-band aliasing components. This output signal is decimated by a factor N to form $U_{i,D}(e^{j\omega})$, and subtracted from the sub-band signal $U_{i,D}(e^{j\omega})$ to obtain the almost alias-free signal $U_{i,D}(e^{j\omega})$. Notice that the sub-band signal $U_{i,D}(e^{j\omega})$ is delayed by $\Delta = K$ samples to compensate for the delay caused by the bandwidth-increased filter $H'_i(e^{j\omega})$. The subtraction causes a spectral dip in $U_{i,D}(e^{j\omega})$, which can be reduced using a minimum-phase filter $G(e^{j\omega})$. The filter signal $U_{i,D}(e^{j\omega})$ is processed by the adaptive sub filter $W_i(e^{j\omega})$. In order to compensate for the effect of the minimum-phase filter, the error signal is filtered by the inverse filter $1/G(e^{j\omega})$.

The inter band aliasing is eliminated from $U_k^d(e^{j\omega})$

$$U_k^d(e^{j\omega}) = \frac{1}{D} \sum_{i=0}^{D-1} H_k \left(e^{\frac{j(\omega-2\pi i)}{D}} \right) U \left(e^{\frac{j(\omega-2\pi i)}{D}} \right)$$

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$$= \frac{1}{D} [H_k(e^{\frac{j(w)}{D}}) U(e^{\frac{j(w)}{D}}) + H_k(e^{\frac{j(w-2\pi k)}{D}}) U(e^{\frac{j(w-2\pi k)}{D}}) + H_k(e^{\frac{j(w-2\pi(k+1))}{D}}) U(e^{\frac{j(w-2\pi(k+1))}{D}})] + \varepsilon_k(e^{jw})$$

Where,

$$\varepsilon_k(e^{jw}) = \frac{1}{D} \sum_{i=0}^{D-1} H_k(e^{\frac{j(w-2\pi i)}{D}}) U(e^{\frac{j(w-2\pi i)}{D}})$$

In order to eliminate aliasing term from $U_k^d(e^{jw})$, the aliasing components should be obtained first. The output signal of the analysis filter is subtracted from the interpolated signal and the result can shown as,

$$U_k^s(e^{jw}) = M \cdot U_k^i(e^{jw}) - U_k(e^{jw})$$

The inter band aliasing components are extracted by passing

$U_k^s(e^{jw})$ through the k th band width-increased analysis filter $H'_k(e^{jw})$, whose magnitude response is almost-flat from $k\pi/D$ to $(k+1)\pi/D$. In general, the frequency interval where the magnitude response of the pass band of the filter bank is almost narrower than that of $H'_k(e^{jw})$ for a perfect re-construction (PR) of the filter bank. This contains unwanted signals in the transition intervals, which will cause another inter-band aliasing component after down sampling.

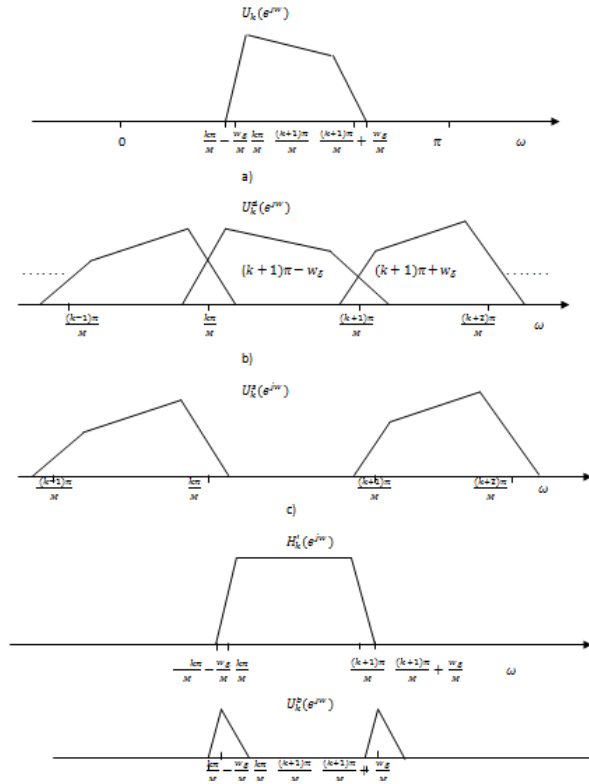


Figure 6: Magnitude responses of the proposed SAF structure. a) Output of the k th analysis filter. b) Interpolated signal of $U_k^d(e^{jw})$ c) Resulting signals after subtracting $U_k(e^{jw})$ from $M \cdot U_k^i(e^{jw})$. d) k th band width increased analysis filter. e) Extracted inter band aliasing component.

BAND WIDTH INCREASED ANALYSIS FILTER BANK

In this band width increased analysis filter bank different constraints and optimization procedures have been proposed, resulting in two main classes of cosine modulated filter banks, namely (i) pseudo-QMF cosine-modulated filter banks and (ii) paraunitary cosine-modulated filter banks.

Pseudo-QMF cosine-modulated filter banks:

(a) Flatness constraint:

The prototype filter $P(z)$ satisfies the following Condition as much as possible

$$|P(e^{j\omega})|^2 + |P(e^{j(\omega-\pi/N)})|^2 \cong 1, \text{ For } 0 < \omega < \pi/N$$

(b) $2N$ th band constraint:

The prototype filter $P(z)$ is a spectral factor of a $2N$ th band filter $Q(z)$, where $Q(z) = P(z) \sim P(z)$, and

$$\sum_{i=0}^{2N-1} Q(zw^i) = 1$$

Let $q(n)$ be the non-causal impulse response of the $2N$ th band filter $Q(z)$, the $2N$ th band constraint can be equivalently written in the time domain as $q(n) = p(n) * p(-n)$ and $q(2Nn) = 1/2N \delta(n)$.

The analysis and synthesis filters of the CMFB are obtained by cosine modulation of the prototype linear-phase low pass filter. If $p(n)$ is the impulse response of the FIR prototype filter, the impulse responses of the k th analysis and synthesis filters $h_k(n)$ and $f_k(n)$ are given respectively as follows:

$$h_k(n) = 2p[n] \cos\left(\frac{\pi}{D}(k+0.5)(n - \frac{L}{2}) + \theta_k\right)$$

$$f_k(n) = 2p[n] \cos\left(\frac{\pi}{D}(k+0.5)(n - \frac{L}{2}) + \theta_k\right)$$

Where L is the order of the prototype filter, and $\theta_k = -1^k \left(\frac{\pi}{4}\right)$ for $k = 0, 1, \dots, M-1$

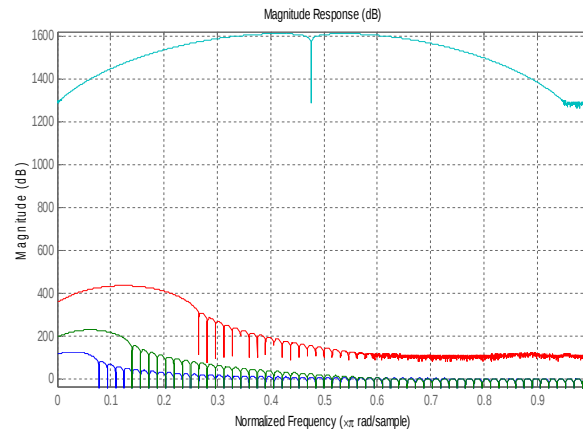


Figure 7: Magnitude response of the 4-channel bandwidth-increased analysis filters.

SIMULATION RESULTS

The implementation and validation of the SAF structure is done in MATLAB version 7.9.0.529. The simulations using the proposed SAF algorithm were performed by varying the number of sub bands that is for $M = 2, 4, 8$, and 16 . The stop band attenuations δ_s , the normalized transition band widths $\frac{w_\delta}{D}$, the orders L of the proto type filters of the CMFBs are described.

White noise

The proposed SAF with critical sampling is evaluated using a white noise input of the length 60000 with unit variance. MSE performance for different sub bands i.e. number of sub bands increases (2, 4, 8, and 16) MSE will decrease.

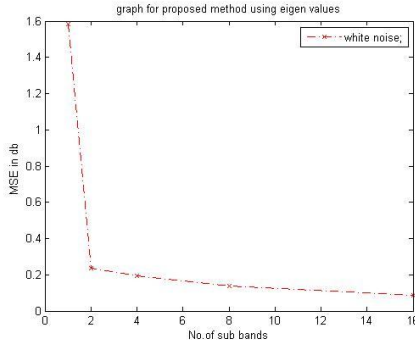


Figure 8: MSE performance for different sub bands

For Speech

Here we use different speech samples like A(f),A(m), F(f),F(m),Had(f),Had(m),New(f),New(m). Where, f means female voice and m means male voice. The figure shows the input speech sample of English alphabet f, which has sampling frequency at 3.6 k Hz. In this paper we compare the spectrum of input speech signal and output speech signal. In this paper we also compare the MSE performance of the proposed SAF structure to those of the other SAF algorithms like auxiliary sub band, sparse sub band method. Our results show that proposed SAF structure has greater convergence and lower MSE than the other algorithms.

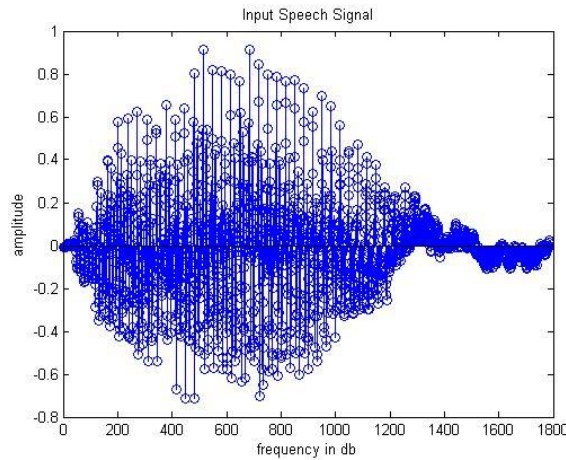


Figure 9: Input speech sample of letter f (f)

The major motivation of using the MSAF structure is to improve the convergence of the NLMS under the speech sample. The mean behavior of the algorithm is depends on the weighted autocorrelation matrix(R_w) which is Eigen vector matrix(R_w) is expectation of the input speech signal. The minimum mean square error $\mathfrak{J}$ is obtained by means of the derivatives

From the above derivations the optimal filter coefficients is given by

$$E \left[d(n)X^*(n-k) - \sum_{l=0}^{p-1} w(l) E[X(n-l)X^*(n-k)] \right] = 0$$

Wherer_{dx}(k) = d(n) X*(n-k), $R_X = E[X(nl)X^*(n-k)]$

From this we are calculate the Eigen value of the input signal. Table 2 represents the Eigen values of sub band adaptive filter when number of sub bands increases. Our results show that when number of sub bands increases Eigen values decreases which will increase the convergence speed.

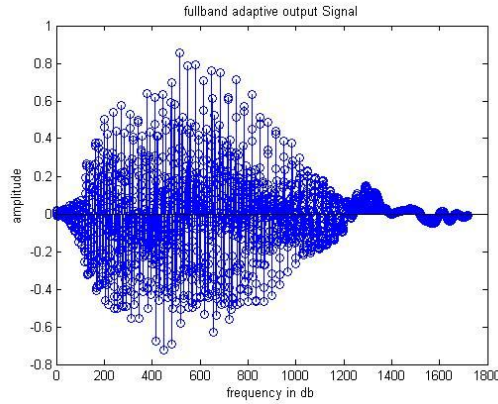


Figure 10: Output of SAF for speech sample of F (f).

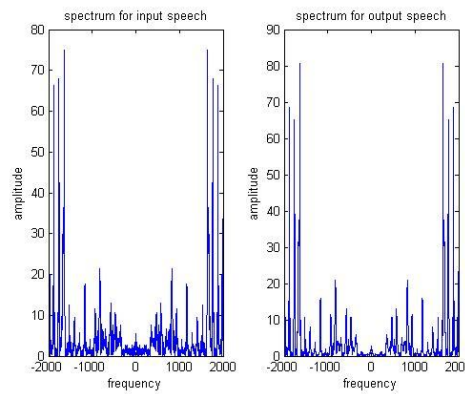


Figure 11: Spectrum of input and Output speech sample F (f)

In our paper we also calculate the PSNR and MSE of a proposed SAF structure. From table 3, 4, and fig. 13 are the performance of proposed SAF with respect to PSNR. In general $PSNR = 10 \log_{10} \left(\frac{\text{information signal power}}{\text{noise power}} \right)$ in db

By using Eigen vector of input and noise signal we can calculate $PSNR = 10 \log_{10} R_x(0)/R_v(0)$

Where $R_x(0)$ =Eigen vector of input signal, $R_v(0)$ = Eigen vector of noise signal.

In our paper, from the above derivations mean square error is calculated as,

$$\begin{aligned} \text{mean square error (MSE)} &= E[|e(k)|^2] = E[e(k)e^*(k)] = E[e(k)d^*(k)] \\ &= E[e(k)(d(k) - \sum_{l=0}^{p-1} w_0(l)X(k-l)^*)] \\ &= E[|d(k)|^2 - \sum_{l=0}^{p-1} w_0(l)E[X(k-l)d(k)^*]] \end{aligned}$$

$$\square = r_d(0)r_{dx}^H w_0 = r_d(0) - r_{dx}^H R_x^{-1} r_{dx}$$

Here $d(n)$ is the desired signal $x(n)$ is the input signal

$\mathfrak{J}$ is the MSE of the error vector and R_x is the eigen vector

r_{dx} is the cross correlation vector

w_0 is optimal coefficient vector

Here in this paper fig 12 and table 5 are represents the MSE performance of a given proposed SAF structure.

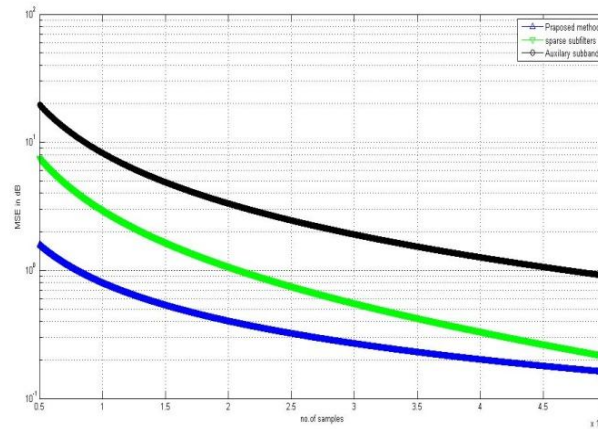


Figure 12: MSE performance of a proposed sub-band adaptive filtering method & auxiliary sub-band method & sparse sub filter methods for several values of M

Table 1: MSE performance of a proposed sub-band adaptive filtering method & auxiliary sub-band method & sparse sub filter methods for several values of M.

Number of samples	Auxiliary sub band method MSE	Sparse sub band method MSE	Proposed sub band method MSE
5000	18.150	7.475	1.561
10000	8.189	2.931	0.795
15000	4.866	1.624	0.532
20000	3.362	1.063	0.400
25000	2.468	0.748	0.319
30000	1.91	0.553	0.266
35000	1.526	0.423	0.228
40000	1.26	0.332	0.200
45000	1.065	0.265	0.177
50000	0.915	0.214	0.164

Table 2: Eigen values of sub band adaptive algorithm for Increase in no of sub bands A smaller Eigen value spread gives a faster convergence rate.

Number of sub bands (N)	Eigen values (λ)				
	White noise	Speech samples			
		A(f)	A(m)	Had(f)	Had(m)
1	1.471	410.9	412.56	415.82	416.94
2	1.488	65.935	67.874	69.635	70.162
4	1.480	16.52	18.024	19.702	19.887
8	1.488	6.327	6.043	6.732	6.394
16	1.486	2.387	2.401	1.975	1.981

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Table 3: Different input speech samples taken from female & male voice of vowels and words sounds, and their PSNR (db) values

Speech samples of vowel & words sounds	Input speech PSNR (db)	Output speech PSNR(db)
a(f)	49.8173	52.3360
a(m)	45.3310	47.5560
f(f)	44.9724	51.3512
f(m)	41.1276	42.4210
had(f)	30.6694	34.4377
had(m)	44.3863	51.1081
new(f)	44.0310	54.0695
New(m)	40.9696	41.3771

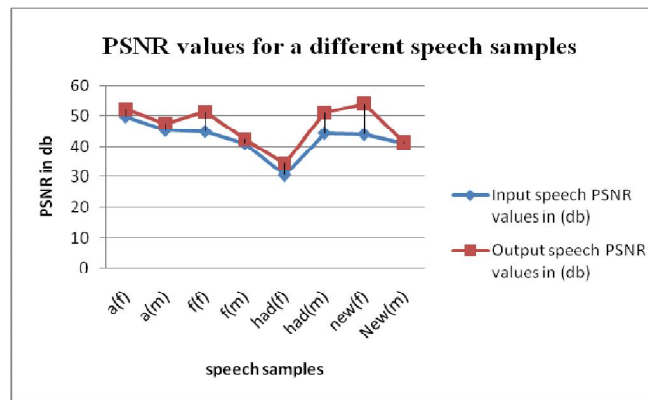


Figure 13: PSNR (db) values in different speech samples

Table 4: Comparison of PSNR values for Existing method vs. proposed method using Eigen values

PSNR values for different speech samples	Speech samples					
	A(f)	A (m)	Had(f)	Had(m)	F(f)	F(m)
Existing method[3]	52.33	47.55	34.43	51.10	51.35	42.42
proposed method	56.67	48.41	37.27	53.43	51.88	42.78

Table 5: Comparison of MSE values for Existing method vs. proposed method with Eigen values

Number of sub bands (M)	MSE performance	
	Existing method [3]	Proposed method
1	1.561	1.123
2	0.532	0.237
4	0.319	0.194
8	0.228	0.138
16	0.177	0.085

The above diagram shows the performance of MSE when number of sub bands increases. Stability of SAF depends or explained (by) on convergence behavior and computational complexity of a structure and design of adaptive FIR filter for the given structure. Stability is ensured for $0 < \mu < 2$. I.e. step size of the adaptive filter (NLMS). Therefore compared to full band structure SAF structure is more stable.

CONCLUSION

In this Paper, in order to fully exploit the benefits of SAF, a Structure with critical sampling that is alias free Inter band structure is proposed. The inter band aliasing is extracted in each sub band using the bandwidth-increased FIR linear-phase analysis filters and then subtracted from each sub band signal. The almost alias-free sub band signals have spectral dips, so the spectral dips are reduced using a filter for the spectral flatness and then the outputs are used for adaptive filtering in each sub band. The computational complexity of the proposed SAF algorithm is reduced. Simulations results show that the proposed sub band structure achieves better convergence rate than the full band structure for speech sample input at lower computational complexity. Because of the decrease in Eigen value spread in sub bands. And our PSNR and MSE results show that proposed new SAF structure performs efficiently.

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