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Efficiency of Oversampled Discrete Fourier Transform Filter Blocks to Cancel Background Noise

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Abstract:
Slow focus ability and complex computations are the main barrages facing the usage of adaptive noise filtering for cancellation of the background noise. Here we have developed noise canceller by using two fold over sampled filter banks. We had formulated the system by few realistic assumptions to analyses the filter. System offers a structure without cross-filters or gap filter banks and hence decreases the residual noise at the output. Increasing initial convergence rate is addressed and computational complexity is analyzed .The performance under white and colored environments, is evaluated in terms of mean square error performance. As a result fast initial convergence was resulted. An increase in the amount of noise reduction by approximately 5dB compared to full-band model reached under actual speech and background noise. In spite of the insertion of analysis/synthesis filter banks, the proposed noise canceller is still computationally efficient.
Key words: Background Noise cancellation, Adaptive Noise Canceling, Gap Filter, DFT Filter.

INTRODUCTION

Noise can seriously damage speech communication especially in noisy environments like crowded streets, factories, noisy rooms. In this article, using the least mean square (LMS) algorithm of adaptive noise filtering and its variants are often used to adapt a full-band filter with a relatively low computation complexity and best performance. However, the full-band LMS solution suffers from significantly degraded performance with colored interfering signals due to the eigen-value spread of the autocorrelation matrix [1]. Moreover, as the length of the adaptive filter is increased, the convergence rate of the LMS algorithm decreases and the computational complexity increases. This can be a problem in applications such as acoustic noise and echo cancellation that demand long adaptive filters to model the path response. These issues are especially important in hand free communication, where processing power must be kept minimum [2]. Sub-band adaptive filtering using multi rate filter banks has been proposed in recent years to speed up the convergence of the (LMS) algorithm and to reduce the computational burden [3],[4]. In this approach, multi rate filter banks are used to split the input signal into a number of frequency bands, each serving as an input to a separate adaptive filter. The sub-band decomposition greatly reduces the update rate of the adaptive filters, resulting in a much lower computational complexity. Therefore, sub-band signals are often down sampled in a sub-band adaptive filter system, this leads to a whitening effect of the input signals and hence an improved convergence behavior [5]. In critically sampled filter banks, the presence of aliasing distortions, requires the use of adaptive cross filters between sub-bands. However systems with cross adaptive filters generally converge slowly and have high computational cost, while gap filter banks produce spectral holes which in turn lead to significant signal distortion [6].In recent literature, the issue of using filter-banks to improve the performance of adaptive filtering is often considered from the view point of application to line echo cancellation in telecommunication systems [7],[8],[9] and [10]. In this paper, an improved sub-band noise cancellation system is derived from an existing full-band model, and then the application to the cancellation of background noise is considered. Few assumptions were made in formulating the system equation and deriving the optimum prototype filter. The proposed oversampled scheme offers a simplified structure that without employing cross-filters or gap filter banks reduces the aliasing level in the sub-bands, and hence decreases the residual noise at the system output. The issue of increasing initial convergence rate is addressed, and the computational complexity of the system is analyzed. The paper is organized as follows: in addition to this section, section 2 gives an overview of noise cancellation setup in adaptive filtering, proposing sub-band scheme to improve performance, section 3 formulates the oversampled sub-band noise canceller ,section 4 gives an efficient implementation arrangement, section 5 analyzes the computational complexity of the system, section 6 gives the optimal prototype filter design procedure, section 7 presents simulation results of the proposed noise canceller, section 8 warps up the paper with conclusion of main aspects.

Sub-band Adaptive Filtering in a Noise Cancellation:

The conventional noise cancellation model is shown in Fig.1, the noisy signal with s symbol is fed through a primary input, while noise with n symbol provides the reference input to the model, n˙ is being added to through a path P(z) producing the desired signal with d symbol, ideally, when steady state is reached, the error signal with symbol should be equal to s .[11]

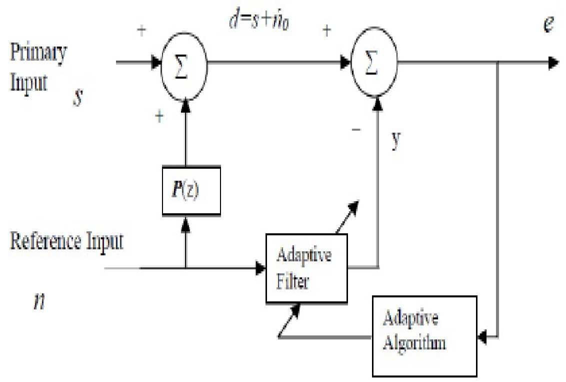

Fig. 1. Basic model of conventional noise canceller

The original model can be extended to sub-band configuration by the insertion of analysis/synthesis filter banks in signal paths as depicted by Fig . 2. Both input signals s and n are fed into identical M-band analysis k filter banks $H_k(z)$ with n˙ being a filtered version of n by an unknown system Here, n represents the background noise, s represents speech and P(z) represents the acoustic noise path, n being correlated with and uncorrelated with s. The ultimate goal is to suppress n˙at the output s^and to retain the non-distorted version of s. After D-fold down-sampling, adaptive filtering is performed in each sub-band separately. Adaptive filter coefficients updating can be done with any kind of algorithm adaptation. However, for robustness and k simplicity the LMS algorithm can be used to update the sub-band filter $\hat{w}_k$. Note that , in contrast to the traditional noise cancellation structure, in this setup is estimated using a set of parallel, independently updated filters $\hat{w}_k$. The outputs of the sub-band adaptive filters y_k is subtracted from the sub-band desired signals ν_k forming the subband errors e_k . These sub-band errors are then up sampled and recombined in the synthesis filter bank $G_k(z)$, leading to the clean output ŝ. Faster initial convergence, and better tracking properties are hoped by splitting signals into sub-bands, and using down-sampling techniques. For colored input signals, with large eigenvalue spread, such as speech and colored noise, full-band adaptation algorithms like the LMS algorithm show slow convergence [12]. In the sub-band case the sub-band signals will have a flatter frequency amplitude spectrum.

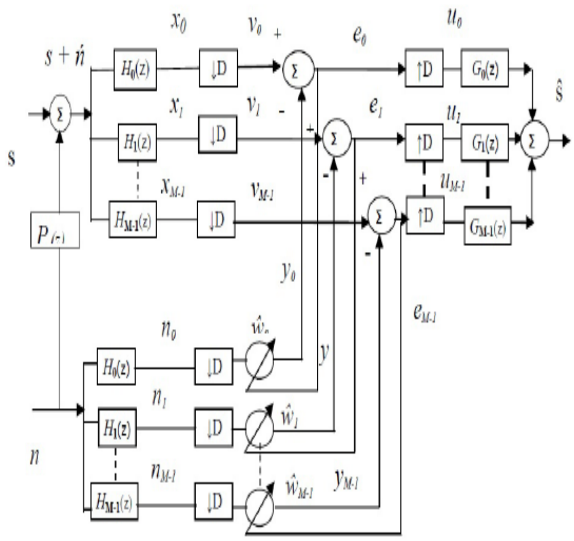

Fig. 2. Block diagram of the Sub-band noise canceller

The step-size of the sub-band adaptive algorithm can be tuned per sub-band, to improve convergence behavior. Another advantage of the sub-band system over the classical full-band adaptation is the reduction in the implementation cost due to the down-sampling. Filter banks can be designed alias-free and perfectly reconstructed when certain conditions are met by the analysis and synthesis filters. However, any filtering operation in the sub-bands may cause a possible phase and amplitude change and thereby altering the perfect reconstruction property. There are tradeoffs in controlling the aliasing effect and the amplitude distortion level; these issues are discussed in [13], with the aim of designing an appropriate prototype filter. Non-critical decimation has been suggested in literature to improve the overall performance of the filter banks Computational savings are maximized whenever the signals are critically down-sampled i. e. M=D,[14]. However, using down-sampling factor less than the number of channels i.e. oversampling has the advantage of permitting the use of moderate order filters as well as lowering the aliasing distortion of the sub-band system. In oversampled sub-band adaptive systems reduced aliasing distortion is trade off for extra computational costs. Depending on the level of oversampling, the cost of computation also increases significantly.

Background Noise Cancellation with Oversampled Discrete Fourier Transform Filter Bank:

Consider the arrangement of Figure 2. The noisy input s+ṅ is divided into subbands with aid of an analysis filter bank according to the following

$$x_k=(s+\dot{n})*h_k(m), k=0,1,2,\ldots,M-1 \quad (1)$$

Where k is the decomposition index, h(m) is the impulse response of an finite impulse response filter FIR, m is a time index, M is the number of sub-bands and (*) is a convolution operator. In a similar manner, the background noise n can be split by an identical set of analysis filters:

$$n_k=n*h_k(m) \quad (2)$$

The background noise is added to the speech via some acoustic path such that:

$$\dot{n}=n*p(m) \quad (3)$$

In z-domain can expressed as:

$$H_k(z)=\sum_{(n=0)}^{(l-1)} h_k(m)z^{(-m)} \quad (4)$$

Where is the filter length Relation (1) can be expressed as:

$$X_k(z)=(S(z)+\dot{N}(z))H_k(z) \quad (5)$$

Similarly, (2) and (3) can be represented in z-domain respectively as:

$$N_k(z)=N(z)H_k(z) \quad (6)$$

$$\dot{N}(z)=N(z)\,P(z) \quad (7)$$

Relation (5) can be expanded to:

$$X_k(z)=S(z)H_k(z)+N(z)H_k(z) \quad (8)$$

Substituting (7) in (8) yields:

$$X_k(z)=S(z)H_k(z)+N(z)P(z)H_k(z) \quad (9)$$

The decimators cause a summation of repeated and expanded spectrum of the input signal according to

$$V_k(z)=\sum_{l=0}^{D-1} X_k(z^{(1/D)}W_D^{\,l}) \quad (10)$$

Assuming the oversampling is sufficient (two foldsucthat only the expanded spectrum of the decomposed signal is exist, this way (10) can be simplified to :

$$V_k(z)=X_k(z^{(1/D)}) \quad (11)$$

Applying this result to (9) ,

$$V_k(z)=S(z^{(1/D)})H_k(z^{(1/D)})+N(z^{(1/D)})P(z^{(1/D)})H_k(z^{(1/D)}) \quad (12)$$

The above relation represents the desired signal to the adaptive filter, now, in a similar analogy we can work out the reference input to the adaptive filter,

$$N_k(z^{(1/D)})= N(z^{(1/D)})H_k(z^{(1/D)}) \quad (13)$$

Consider the adaptation process in each individual branch according to Figure 2, and let us define e(m) as the error signal, y(m) is the output of the adaptive filter calculated at the down-sampled rate (Dm),ŵ(m) is the filter coefficient vector at m th iteration, ì is the adaptation step-size factor , á is proportional to the inverse of the power input to the adaptive filter, and m is a dummy time index, then we have

$$y_k(m)=\hat{W}_k^{\,T}(m)n_k(m) \quad (14)$$

$$e_k(m)=v_k(m)-y_k(m) \quad (15)$$

$$\hat{W}_k(m+1)=W_k(m)+\mu_k.a_k.e_k(m)n_k(m) \quad (16)$$

Relation (16) represents the branch update of the sub-band adaptive filter In z-domain, relation (15) can be expressed as:

$$E_k(z)=V_k(z) - Y_k(z) \quad (17)$$

Substituting for $V_k(z)$ from (12)

$$E_k(z)=S(z^{(1/D)})\,H_k(z^{(1/D)})+N(z^{(1/D)})P(z^{(1/D)})\,H_k(z^{(1/D)})-Y_k(z) \quad (18)$$

This can be expressed as

$$E_k(z)=S_k(z)-\hat{Y}_k(z)-Y_k(z) \quad (19)$$

Where $S_k(z)=S(z^{(1/D)})Hk(z^{(1/D)})$ and $\hat{Y}_k(z)=N(z^{(1/D)})P(z^{(1/D)})Hk(z^{(1/D)})$,The aim of the adaptation process is to suppress $\hat{Y}_K$ (z) by equating it to $Y_k(z)$ leaving $S_k(z)$ undistorted. Each sub-band error signal is then interpolated by up sampling and synthesis filtering. The interpolators have a compressing effect according to

$$U_k(z)= E_k(z^D) \quad (20)$$

This will restore the spectrum of the sub-band signals, and hence terms in (18), to their original frequency range i.e. to the situation before decimation. Unfortunately, we will have an imaging effect due to up sampling , this can be removed from sub-band signals by suitably designed synthesis filters $G_k(z)$ the output signal now can be reconstructed and we can state the input/output relationship as

$$\hat{S}_k(z)=\sum_{K=0}^{M-1} G_k(z)U_k(z) \quad (21)$$

Where $U_k(z)=S(z)H_k(z)+N(z)P(z)H_k(z)-Y_k(z)$ (22)

Let $R_k(z)=N(z)P(z)H_k(z)-Y_k(z)$ (23)

Where R(z) represents the system residual noise On steady state, R(z) should be very small, and relation (21) can be modified to

$$\hat{S}_k(z)=S(z)\sum_{K=0}^{M-1} G_k(z)\,U_k(z) \quad (24)$$

The branch filters $H_k(z)$,and $G_k(z)$ can be derived from prototype filters $H_0(z)$,$G_0(z)$ according to $H_k(z)=H_0(zW_M^k)$, and $G_k(z)=G_0(zW_M^k)$, thus forming a DFT filter bank ,[15]. Where $W_M=e^{-j2\pi/M}$ .The term in $\sum_{l=0}^{M-1}G_k(z)H_k(z)n$ (24) represents the distortion due the insertion of the analysis/synthesis filter bank. Let A(z) be the distortion function ,in frequency domain, A(z) can be represented as

$$A(e^{j\omega})=\sum_{k=0}^{M-1} H_k(e^{j\omega})\,G_k(e^{j\omega}) \quad (25)$$

The objective is to find prototype filter coefficients h(m,) and g(m) to minimize $A_d(z)$ According to

$$A_d=\max \omega(1-|A(e^{j\omega})|) \quad (26)$$

Relaxing the perfect reconstruction property, tolerating small amplitude distortion, we can have frequency selective filters in a near perfect reconstruction NPR filter bank [16]

Computationally Efficient Implementation of Background Noise Canceller:

From Fig. 2 it can be seen that the analysis filters are immediately followed by down-samplers. Hence it is cheaper to do all filtering operations at the down-sampled rate. Efficient implementation of DFT modulated filter banks can be done using poly phase decomposition of a prototype filter and fast Fourier transform (FFT).

A DFT modulated analysis filter bank with subsequent D-fold down-sampling can be implemented as a tapped P delay line with D - fold down-sampling, followed by poly phase components of the prototype filter $H_p(z)$ as shown in Fig. 4. The synthesis bank is constructed in a similar fashion with inverse DFT. The analysis prototype filter $H_0(z)$ can be represented in polyphase components as follows

$$H_0(z)=\sum_{p=0}^{M-1}z^{-k}H_p(z^D) \quad (27)$$

The transfer function of the pth polyphase filter $H_p(z)$ is given by:

$$H_p(z)=\sum_{m=0}^{L-1} h_p(m)z^{-m} \quad (28)$$

Where: $h_p(m)=h_p(mD+p),0\le p\le M-1$,Lis is the filter length.

$$G_0(z)=\sum_{p=0}^{M-1} G_p(z^D)\,z^{-(M-1-k)} \quad (29)$$

Effectively, the number of poly phase components is equal to the number of sub-bands i.e. p=k Fig .3 depicts an efficient implementation of the proposed noise canceller.

Computational Efficiency of the Oversampled Sub-band Noise Canceller:

The total computational complexity of the sub-band noise canceller consists of two parts: the complexity. due the insertion of the filter bank C_{FB} and the complexity for the adaptive filtering C_{AF} We assume that the input signals and are real signals, the analysis and synthesis filtering is implemented with the poly phase uniform DFT filter bank. The prototype analysis/synthesis filter is of length L , and that M/D is an integer. C_{FB} is calculated as follows. There are a total of M poly phase filters, each of length L/D operating at a rate of 1/D in the filter bank thus requiring LM/D^2 real multiplications per input sample. This operation is performed three times, for the analysis filtering of s and n ,and for the synthesis filtering of $e_0,e_1,\ldots,e_{M-1}$.

The M-point DFT and IDFT are implemented with a radix-2 FFT which requires approximately $M/2\log_2 M-M$ complex multiplications. For real data, the M-point DFT can be realized with an M/2-point FFT and M/2 complex multiplications. This results in $M/2\log_2 M/2$ real multiplications for the analysis filtering of s and n. A similar realization holds for the synthesis filtering of $e_1,\ldots,e_{M-1}$. Thus the total number of real multiplications for sub-band filtering per input sample is

$$C_{FB}=3LM/D^2+3M\log_2 M/2 \quad (30)$$

Since the input and the desired signals are real, we can use the symmetry property of the DFT to process only (M/2) +1 of the sub-bands . Assuming the length of the impulse response to be modeled by the adaptive filter is L_A, each sub-band adaptive filter is of length L_A

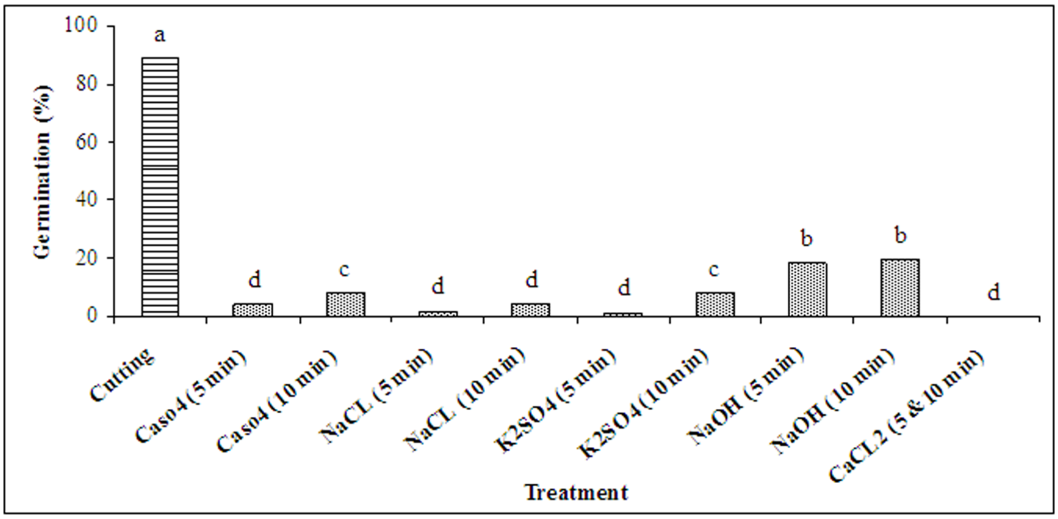

Fig. 3. Efficient implementation of background noise canceller, H_(p) (z),G_(p) (z)are polyphase component of analysis and synthesis filters respectively.

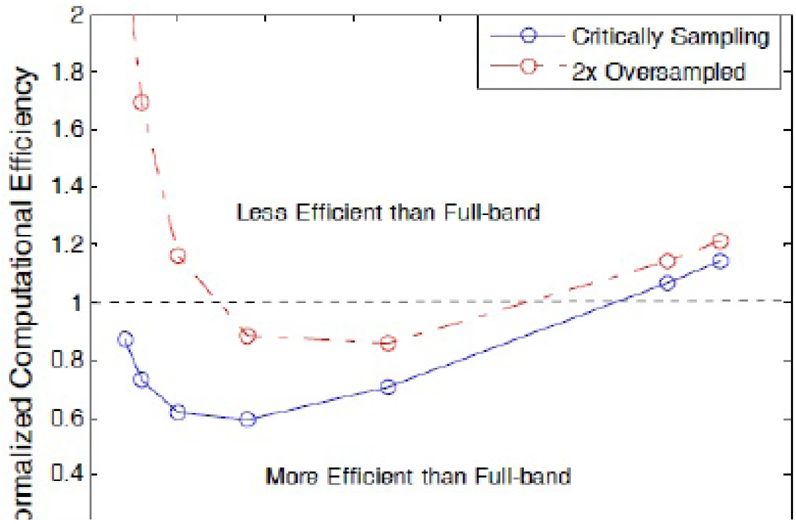

Fig. 4. Computational complexity of the sub-band noise canceller In a similar way the prototype synthesis filter G_(0) (z) can be expressed in poly phase form using type 2 poly phase representations, thus reducing the implementation cost.

/D operating at the down-sampling rate, and the LMS algorithm is used for the update . The total number of multiplications for adaptive filtering per input sample is

$$C_{AF}=2(2L_A)/D+1)+4(M/2-1)(2L_A)/D+1)/D \qquad (31)$$

T The total computational complexity C_T for the M/D oversampled, M-band noise canceller is then taken as the sum of the filter bank complexity and the adaptive filter complexity

$$C_T=(3LM+4ML_A-4L_A/D^2 + (2M-2)/D+ 3M \log_2 M/2 \qquad (32)$$

According to relation (32), the normalized computational complexity ($C_{subband}$ /$C_{fullband}$) versus the A number of sub-band can be plotted as shown in Figure 4, values of L,and L_A are 128 and 512 respectively. It can deduced that critically sampled systems with 4,8,16,32 sub-bands are computational more efficient than the equivalent full-band system. On the other hand, the 2×oversampled system are computationally efficient with 16 or 32 sub-bands.

Prototype Filter Design:

A typical FIR causal prototype filter can be defined by the transfer function given by (4).The impulse response h(m) of this filter is truncated by multiplying by a window function w(m)

$$h(m)=\sin(2\pi f_e (m-(L-1)/2))/\pi(m-(L-1)/2)\ w(m) \quad (33)$$

For a given number of sub-bands,M, and for a given sub-sampling factor D, and for a certain length of prototype filter,L, we design the normalized cut-off frequency 0<f< ½ and the corresponding window function.

There are several window types that can be investigated and used to design the prototype filters, examples of these windows are the Hamming, Kaisar ,Van-Hann ,and the Dolph-Chebyshev , also algorithms such as the Remez exchange can also be exploited for the same purpose. The Kaisar, and the Dolph-Chebyshev windows have been reported to have a good performance in the presence of aliasing [13]. However, these methods possess additional design parameters which should be controlled in the optimization problem. In this paper, since we are highly oversampling, we assume sufficient sub-band separation between sub-bands does exist, hence negligible aliasing power, so, we focus on the use Hamming window for simplicity. The Hamming window is defined as:

$$w(m) = \begin{cases} \beta - (1-\beta)\cos\frac{2\pi n}{L-1} & For\ m = 0,1,2,\dots,L-1 \\ 0 & otherwise \end{cases} \quad (34)$$

Where β = 0.54 ,We assume the same prototype filter for the analysis and the synthesis filter banks. In order to control the amplitude distortion the final optimization can be formulated as

$$A_d^{min}(h(\gamma)) \quad (35)$$

Where γ is one dimensional variabl. Minimizing (35) within a tolerance yields a prototype filter in a near perfect reconstruction filter bank.

Simulation Results:

Prototype filter was designed using Hamming window with cut-off frequency specifications. Optimization parameters are shown in table 1 .The magnitude frequency response of filter bank is depicted in Fig.5. The acoustic noise path used in these test is an approximation of small room impulse response modeled by a finite impulse response processor of 512 taps. To measure the convergence behavior of the sub-band noise canceller, a variable frequency sinusoid was corrupted with white Gaussian noise. This noise was passed through a transfer function representing the acoustic path. The corrupted signal is then applied to the primary input of the noise canceller, regarding zero mean, white Gaussian noise was applied to the reference input. A sub-band power normalized version of the LMS algorithm is used for adaptation. Simulation parameters are listed in Table 2, and the simulation flow chart is given by Fig. A in section 7. Mean square error MSE convergence is used as a measure of performance. Plots of MSE were produced and smoothed with a suitable moving average filter. A comparison is made with a conventional full-band system as well as with a critically sampled as shown in Fig.6.

To test the behavior under environmental conditions, a speech signal is then applied to the primary input of the proposed noise canceller. The speech was in the form of English utterance “Vacancy, One, Two, Three” spoken by a women as shown in Fig.7,this speech was sampled at 8 kHz . Machinery noise was used as a background interference to corrupt the above speech as shown in Fig.8. Mean square error plots are produced as shown in Fig.9, in this figure, convergence plots of a full-band and critically sampled systems are also depicted for comparison. For sake of clarity, and due to high density of the graphs, Fig.9 is reproduced as in Fig.10 with the plot of critically sampled system was dismissed since it is sufficient to compare with conventional full-band model.

The first advantage of these tests is the gain in computational efficiency. However, as the down sampling factor reduced from critical case D=M , to the two fold oversampled situation ,where D=M/2 , the computational burden is greatly increased ,but for sub band decomposition of 16 band it is still less than the cost of conventional full-band system, As this is clear from Figure 4.From Fig.6, it is clear that the mean square error MSE plot of the oversampled sub-band system converges faster than the critically sampled and full-band systems. While the full-band system is still converging in slow asymptotic way, the oversampled noise canceller approaches 25 dB noise reductions in about 2500 iterations. In an environment where the impulse response of the noise path is changing over a period of time shorter than the initial convergence period, as in the case considered in this paper, initial convergence will most affect cancellation quality. On the other hand, the critically sampled case needs 10000 iterations to reach the same level, this is obviously due to the inability to model properly in the presence of aliasing, With the two fold oversampling, reduced aliasing levels is a tradeoff for extra computations.

Finally, Fig.9 contains the mean square error plots for oversampled, critically sampled and full-band systems under speech and colored background noise inputs. In this case it is clear that the full-band system cannot model properly with colored noise as the input to the adaptive filters, and the residual error can be sever when the environment noise is highly colored which was proved to be true in these simulations. Tests performed in this part of the experiment proved that the oversampled sub-band noise canceller does have better performance than the full-band system. It is evident from Fig.10 that the proposed system achieves 5 dB noise reductions better than the conventional single rate full-band system.

Table1. Design parameters of pro type filter

Window type	Hamming
Cut off frequency normalized	0.0313
Number of sub bands ,M	16
Down sampling factor, D	8
Length of pro type filter, L	128

Tale2. Simulation parameters of noise canceller tests

Analysis filter bank type	Poly phase DFT, even stacking
Synthesis filter bank type	Poly phase DFT, even stacking
Acoustic noise path	FIR processor with 512 taps
Adaptation algorithm type	Sub band normalized power LMS
Adaptation parameters	0.02
Primary input (first test)	Variable frequency sinusoid
Reference input (first type)	Additive white Gaussian noise, with zero mean and unit variance
Primary input (second test)	English Utterance Vacancy, One, Two, Three Sampled at 8KHz
Reference input (second type)	Machinery noise ,sampled at 8KHz
Performance measure method	Total MSE convergence

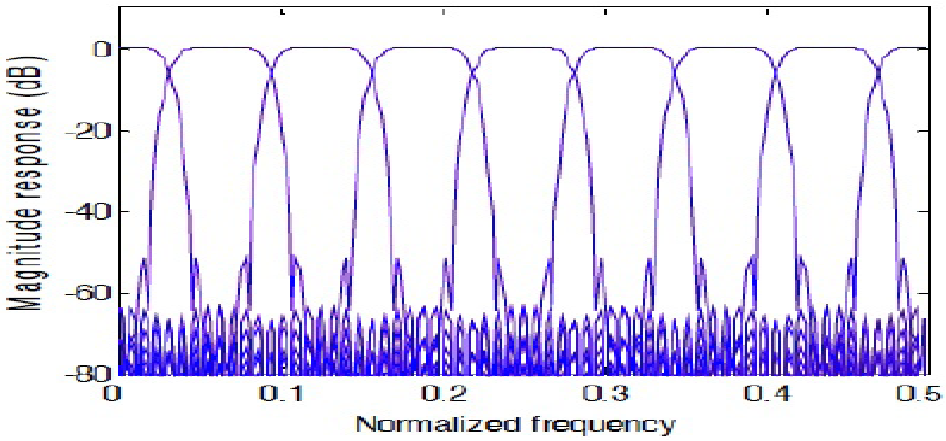

Fig. 5. Magnitude frequency response of DFT filter bank (even stacking)

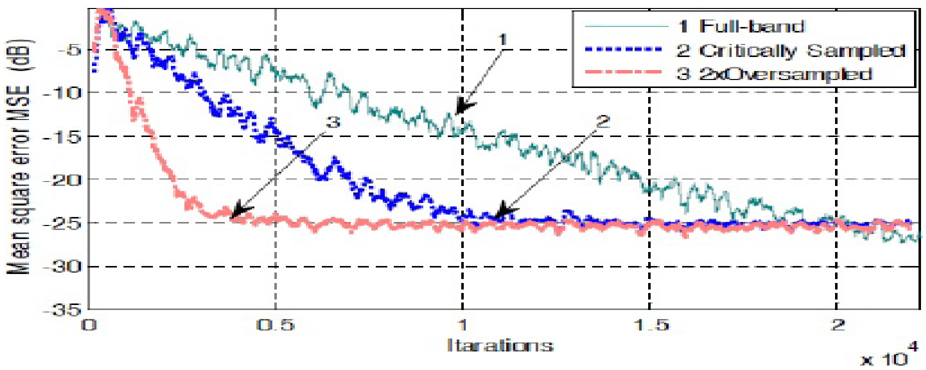

Fig. 6. Mean square error performance of the oversampled noise canceller compared to conventional full-band, and critically sampled systems, under white input.

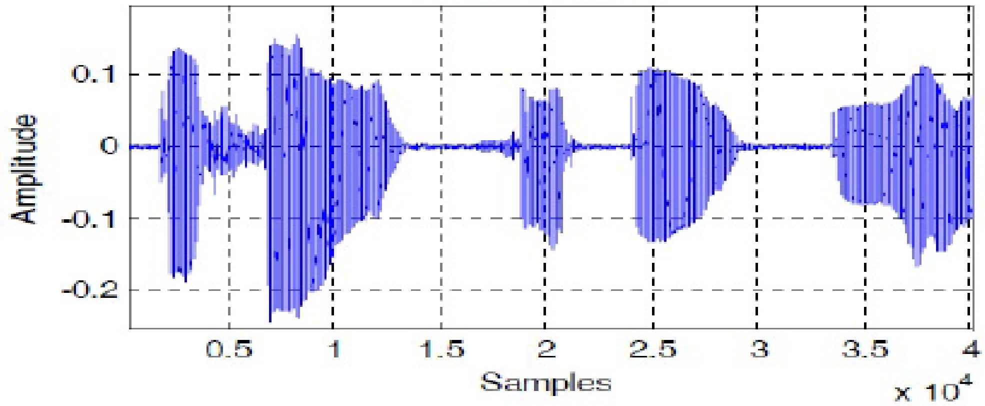

Fig. 7. English utterance “Vacancy, One, Two, Three” spoken by a woman.

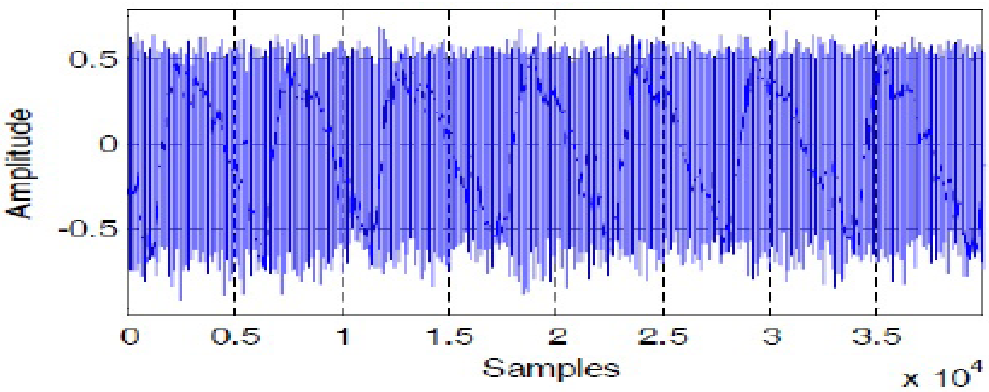

Fig. 8. Machinery noise as a background interference.

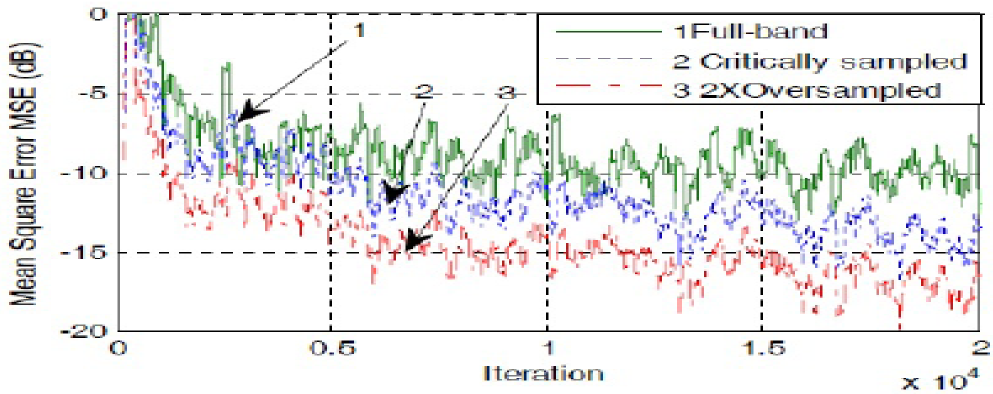

Fig. 9. MSE convergence under actual speech and background interference.

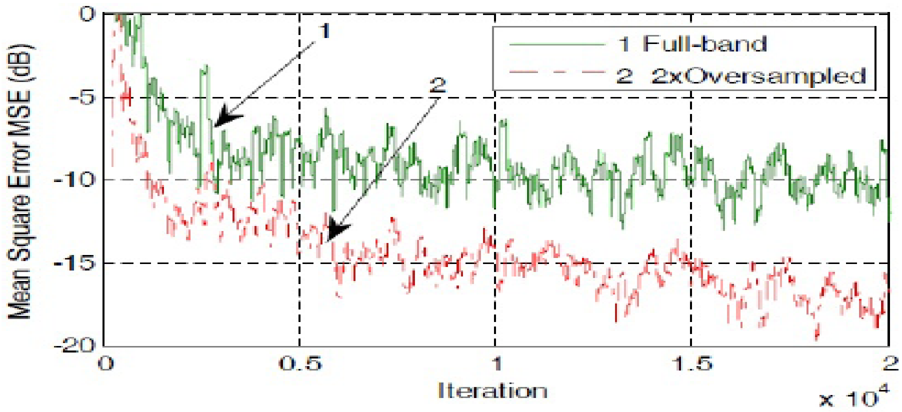

Fig. 10. Comparison of MSE for the two fold oversampled with a conventional full-band system.

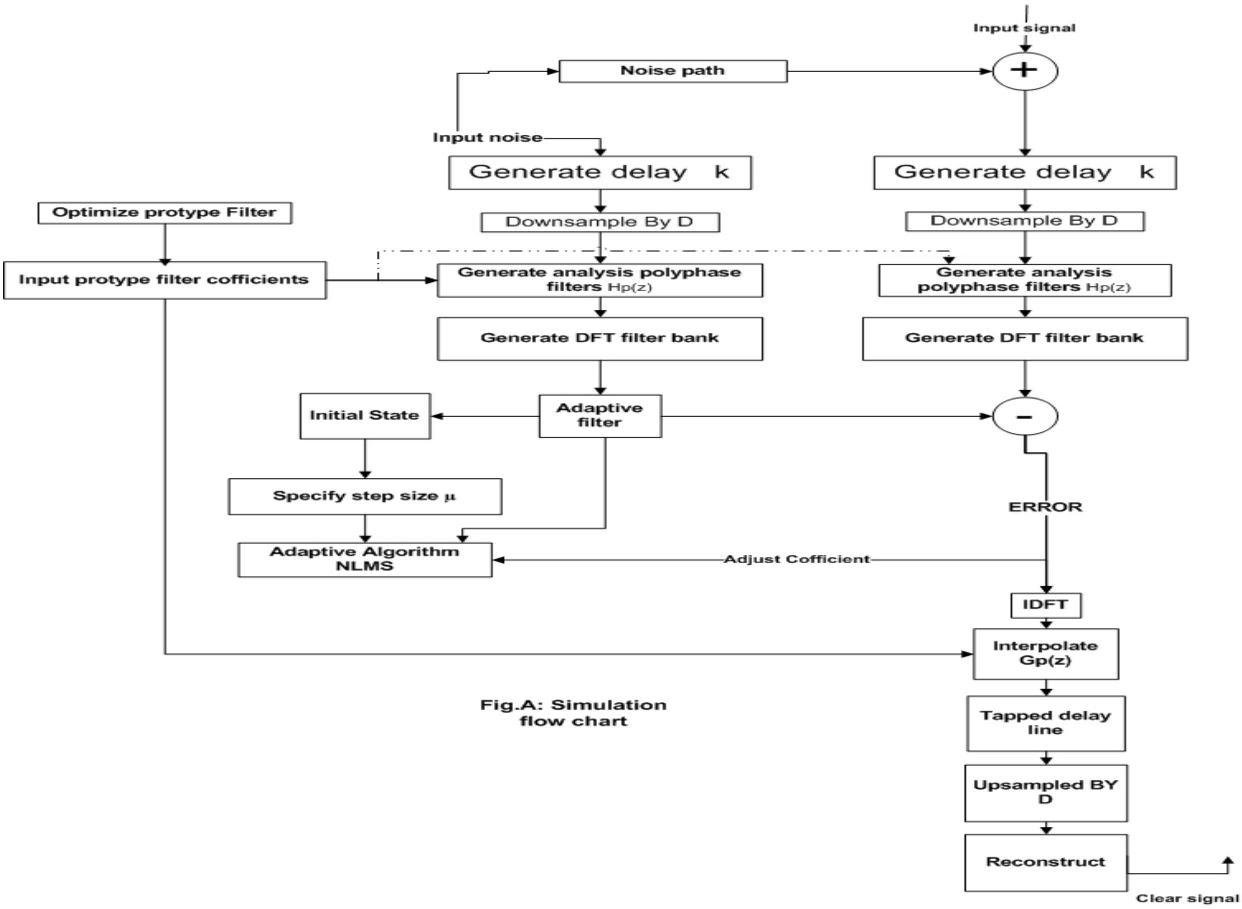

Fig.A. Simulation Flow chart

CONCLUSIONS

In this work, an oversampled sub-band noise canceller is developed to overcome the problems of slow convergence and increased computational complexity. An efficient optimized two fold oversampled DFT filter bank was used in the canceller; the computational efficiency of system is analyzed. The system has shown better performance compared to the conventional full band model as well to the critically sampled scheme. The convergence behavior under white and colored environments is greatly improved. An increase in the amount of noise reduction by approximately 5dB compared to full-band model was reachable under actual speech and background noise. In spite of the insertion of analysis/synthesis filter banks, the system is still computationally efficient.

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