

Development of a Background Noise Cancellation System Using Efficient Oversampled DFT Filter Banks

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Abstract: Slow convergence and high computational complexity are the main problems incorporating with use of conventional adaptive noise filtering when applied to reduce the background in speech communication. In this paper, an improved background noise canceller for speech signals is developed, the canceller is derived by inserting an efficient two fold oversampled filter banks in the conventional fullband model. Proposed system equation is formulated with few realistic assumptions to ease analyzing and deriving an optimum prototype filter. The proposed oversampled system offers a simplified structure that without employing cross-filters or gap filter banks reduces the aliasing level in the subbands, and hence decreases the residual noise at the system output. The issue of increasing the initial convergence rate is addressed, and the computational complexity of the system is analyzed. The performance under white and colored environments is evaluated in terms of mean square error performance. Remarkably fast initial convergence was obtained. Moreover an increase in the amount of noise reduction by approximately 5dB compared to fullband model was reachable 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: Noise cancellation, Adaptive Filtering, Multirate Filter Banks, DFT Filter Banks, Subband Decomposition, Polyphase Representation

INTRODUCTION

Background noise can seriously damage speech communication especially in noisy environments like streets, factories noisy rooms. In this context, adaptive noise filtering using the least mean square (LMS) algorithm and its variants are often used to adapt a fullband filter with a relatively low computation complexity and good performance. However, the fullband LMS solution suffers from significantly degraded performance with colored interfering signals due to the eigenvalue spread of the autocorrelation matrix (Haykin, 2002). 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 (Johnson *et al.*, 2004).

Subband adaptive filtering using multirate filter banks has been proposed in recent years to speed up the convergence of the least mean square (LMS) and to reduce the computational burden (Pradhan and Reddy, 1999),(Petraglia and Batalheiro, 2008). In this approach, multirate 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 subband decomposition greatly reduces the update rate of the adaptive filters, resulting in a much lower computational complexity. Furthermore, subband signals are often downsampled in a subband adaptive filter system, this leads to a whitening effect of the input signals and hence an improved convergence behavior (Gilloir and Vetterli, 1992).

In critically sampled filter banks, the presence of aliasing distortions requires the use of adaptive cross filters between subbands. However systems with cross adaptive filters generally converge slowly and have high

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computational cost, while gap filter banks produce spectral holes which in turn lead to significant signal distortion (Akansu and Smith, 1995). 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 (Breining *et al.*, 1999), (Chin and Boroujeny, 2001), (Choi and Bae, 2007), (Mingsian *et al.*, 2008) and (Schüldt *et al.*, 2008). In this paper, an improved subband noise cancellation system is derived from an existing fullband 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 subbands, 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 performance under white and colored environments is evaluated in terms of mean square error performance. The paper is organized as follows: in addition to this section, section 2 gives an overview of adaptive filtering in a noise cancellation setup, proposing subband scheme to improve performance, section 3 formulates the oversampled subband 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 wraps up the paper with conclusion of main aspects.

2. Subband Adaptive Filtering in a Noise Cancellation Setup:

The conventional noise cancellation model introduced by Widrow and Hoffs (Widrow and Stearns, 1985) is shown in Figure 1, the noisy signal s is fed through a primary input, while noise n provides the reference input to the model, \hat{n} is being added to s through a path $P(z)$ producing the desired signal d , ideally, when steady state is reached, the error signal e should be equal to s .

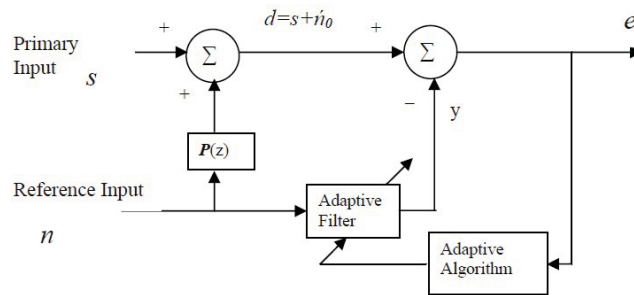


Fig. 1: Conventional noise cancellation model

The original model can be extended to subband configuration by the insertion of analysis/synthesis filter banks in signal paths as depicted by Figure 2. Both input signals s and n are fed into identical M -band analysis filter banks $H_k(z)$, with \hat{n} being a filtered version of n by an unknown system $P(z)$. Here, n represents the background noise, s represents speech and $P(z)$ represents the acoustic noise path, n being correlated with \hat{n} and uncorrelated with s . The ultimate goal is to suppress \hat{n} at the output \hat{s} and to retain the non-distorted version of s . After D -fold downsampling, adaptive filtering is performed in each subband separately. Adaptive filter coefficients updating can be done with any kind of algorithm adaptation. However, for robustness and simplicity the LMS algorithm can be used to update the subband filters \hat{w}_k . Note that in contrast to the traditional noise cancellation structure, in this setup $P(z)$ is estimated using a set of parallel, independently updated filters \hat{w}_k . The outputs of the subband adaptive filters y_k is subtracted from the subband desired signals v_k forming the subband errors e_k . These subband errors are then upsampled and recombined in the synthesis filter bank $G_k(z)$, leading to the clean output \hat{s} .

Faster initial convergence, and better tracking properties are hoped by splitting signals into subbands, and using downsampling techniques. For colored input signals, with large eigenvalue spread, such as speech and colored noise, fullband adaptation algorithms like the LMS algorithm show slow convergence (Sheikhzaheh *et al.*, 2003). In the subband case the subband signals will have a flatter frequency amplitude spectrum.

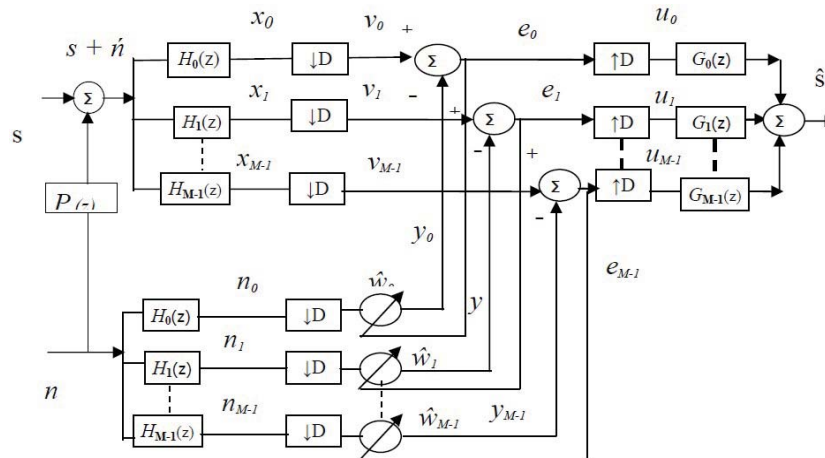


Fig. 2: The Subband noise canceller

The step-size of the subband adaptive algorithm can be tuned per subband, to improve convergence behavior. Another advantage of the subband system over the classical fullband adaptation is the reduction in the implementation cost due to the downsampling.

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 subbands 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 (Cedric *et. al.*, 2006) 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 (Harteneck *et. al.*, 1998) Computational savings are maximized whenever the signals are critically downsampled i. e. $M=D$. However, using downsampling 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 subband system. In oversampled subband 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.

3. Background Noise Cancellation with Oversampled Discrete Fourier Transform DFT Filter Bank:

Consider the arrangement of Figure 2. The noisy input $s+\hat{n}$ is divided into subbands with aid of an analysis filter bank according to the following

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

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 subbands and $(*)$ is a convolution operator. In a similar manner, the background noise n can be split by an identical set of analysis filters:

$$n_k = n * h_k(m) \tag{2}$$

The background noise \hat{n} is added to the speech via some acoustic path $p(m)$ such that:

$$\hat{n} = n * p(m) \tag{3}$$

In z-domain $h(m)$ can be expressed as:

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

Where L is the filter length

Relation (1) can be expressed as:

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

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

$$N_k(z) = N(z) H_k(z) \tag{6}$$

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

Relation (5) can be expanded to:

$$X_k(z) = S(z) H_k(z) + \dot{N}(z) H_k(z) \tag{8}$$

Substituting (7) in (8) yields:

$$X_k(z) = S(z) H_k(z) + N(z) P(z) H_k(z) \tag{9}$$

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

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

Assuming the oversampling is sufficient (two fold $D=M/2$) such that only the expanded spectrum of the decomposed signal is exist, this way (10) can be simplified to

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

Applying this result to (9)

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

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,

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

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 downsampled rate(Dm), $\hat{w}(m)$ is the filter coefficient vector at m th iteration, μ is the adaptation step-size factor, α is proportional to the inverse of the power input to the adaptive filter, and m is a dummy time index, then we have

$$y_k(m) = \hat{w}_k^T(m) \mathbf{n}_k(m) \tag{14}$$

$$e_k(m) = v_k(m) - y_k(m) \tag{15}$$

$$\hat{w}_k(m+1) = \hat{w}_k(m) + \mu_k \cdot \alpha_k \cdot e_k(m) \mathbf{n}_k(m) \tag{16}$$

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

$$E_k(z) = V_k(z) - Y_k(z) \tag{17}$$

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

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

This can be expressed as $E_k(z) = S_k(z) - \hat{Y}_k(z) - Y_k(z)$ (19)

Where $S_k(z) = S(z^{1/D})H_k(z^{1/D})$, and $\hat{Y}_k(z) = N(z^{1/D})P(z^{1/D})H_k(z^{1/D})$

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 subband error signal is then interpolated by upsampling and synthesis filtering. The interpolators have a compressing effect according to

$$U_k(z) = E_k(z^D) \tag{20}$$

This will restore the spectrum of the subband 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 upsampling, this can be removed from subband 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

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

Where

$$U_k(z) = S(z)H_k(z) + N(z)P(z)H_k(z) - Y_k(z) \tag{22}$$

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

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

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 (Vaidyanathan, 1990).

Where $W_M = e^{-j2\pi/M}$

The term $\sum_{k=0}^{M-1} G_k(z)H_k(z)$ in (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

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

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

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

Relaxing the perfect reconstruction property, tolerating small amplitude distortion, we can have frequency selective filters in a near perfect reconstruction NPR filter bank (Saramaki and Bregovic, 2001).

Computationally Efficient Implementation of Background Noise Canceller:

From Figure. 2 it can be seen that the analysis filters are immediately followed by downsamplers. Hence it is cheaper to do all filtering operations at the downsampled rate. Efficient implementation of DFT modulated filter banks can be done using polyphase decomposition of a prototype filter and fast Fourier transform (FFT). A DFT modulated analysis filter bank with subsequent D-fold downsampling can be implemented as a tapped delay line with D - fold downsampling, followed by polyphase components of the prototype filter $H_p(z)$ as shown in Figure 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

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

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

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

Where;

$$h_p(m) = h(mD + p) , 0 \leq p \leq M-1 , L \text{ is the filter length.}$$

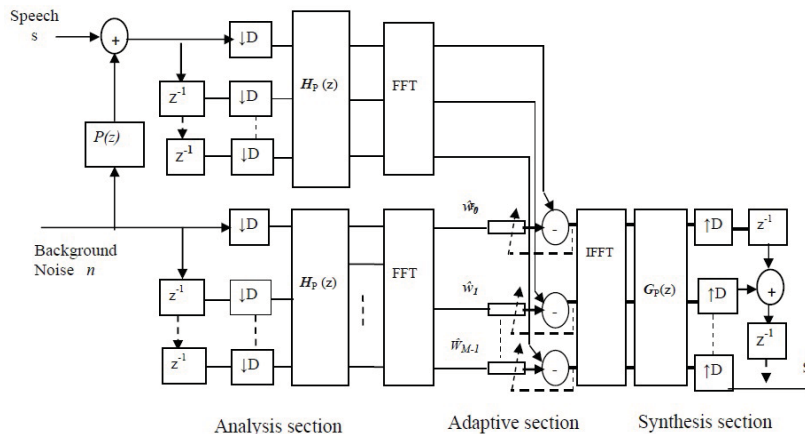


Fig. 3: Efficient implementation of background noise canceller, $H_p(z)$, $G_p(z)$ are polyphase component of analysis and synthesis filters respectively.

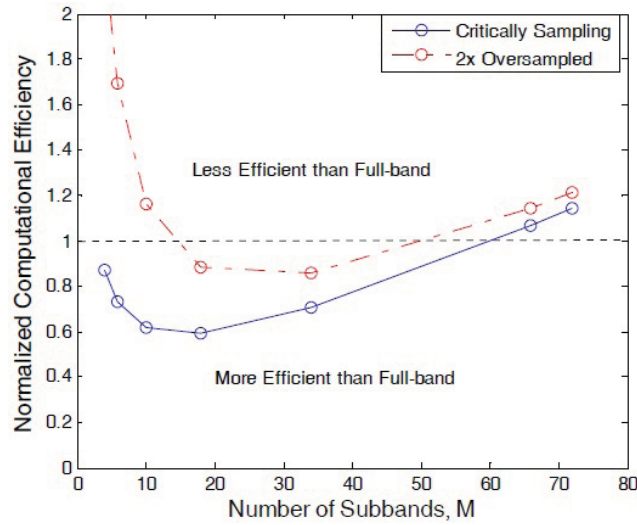


Fig. 4: Computational complexity of the subband noise canceller

In a similar way the prototype synthesis filter $G_0(z)$ can be expressed in polyphase form using type 2 polyphase representations, thus reducing the implementation cost.

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

Effectively, the number of polyphase components is equal to the number of subbands i.e. $p=k$. Figure 3 depicts an efficient implementation of the proposed noise canceller.

Computational Efficiency of the Oversampled Subband Noise Canceller:

The total computational complexity of the subband 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 s and n are real signals, the analysis and synthesis filtering is implemented with the polyphase 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 polyphase 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, \dots, e_{M-1} . The M -point DFT and IDFT are implemented with a radix-2 FFT which requires approximately $\frac{M}{2} \log_2 M - M$ 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 $\frac{M}{2} \log_2 M / 2$ real multiplications for the analysis filtering of s and n , a similar realization holds for the synthesis filtering of e_0, \dots, e_{M-1} . Thus the total number of real multiplications for subband filtering per input sample is

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

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 subbands . Assuming the length of the impulse response to be modeled by the adaptive filter is L_A , each subband adaptive filter is of length L_A/D operating at the downsampling rate, and the LMS algorithm is used for the update . The total number of multiplications for adaptive filtering per input sample is

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

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

$$C_T = \frac{3LM + 4ML_A - 4L_A}{D^2} + \frac{2M - 2}{D} + 3M \log_2 \frac{M}{2} \tag{32}$$

According to relation (32), the normalized computational complexity ($C_{subband} / C_{fullband}$) versus the number of subband 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 subbands are computational more efficient than the equivalent full-band system. On the other hand, the $2\times$ oversampled system are computationally efficient with 16 or 32 subbands.

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 $w(m)$

$$h(m) = \frac{\sin(2\pi f_c(m - (L - 1) / 2))}{\pi(m - (L - 1) / 2)} w(m) \tag{33}$$

For a given number of subbands, M , and for a given subsampling factor D , and for a certain length of prototype filter, L , we design the normalized cut-off frequency $0 < f_c < 1/2$ and the corresponding window function. There are several window types that can be investigated and used to design the prototype filters, examples of these widows are the Hamming, Kaiser ,Van-Hann ,and the Dolph-Chebyshev , also algorithms such as the Remez exchange can also be exploited for the same purpose. The Kaiser, and the Dolph-Chebyshev windows have been reported to have a good performance in the presence of aliasing (Cedric PERLINK<http://et.alet. al., 2006>). 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 subband separation between subbands does exist, hence negligible aliasing power, so, we focus on the use Hamming window for simplicity. The Hamming window is defined as

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

Where $\beta = 0.54$

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

$$A_d(h(\gamma)) \tag{35}$$

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

Simulation Results and Discussion:

Prototype filter was designed using Haming window with cut-off frequency specifications. Optimization parameters are shown in table 1 .The magnitude frequency response of filter bank is depicted in Figure 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 subband 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 subband 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 Figure A in appendix A. 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 fullband system as well as with a critically sampled as shown in Figure 6.

Table 1: Design parameters of prototype filter

Window type	Haming
Cut off frequency normalized	0.0313
Number of subbands, M	16
Downsampling factor, D	8
Length of prototype filter, L	128

Table 2: Simulation parameters of noise canceller tests.

Analysis filter bank type	Polyphase DFT ,even stacking
Synthesis filter bank type	Polyphase IDFT ,even stacking
Acoustic noise path	FIR processor with 512 taps
Adaptation algorithm type	Subband normalized power LMS
Adaptation parameters μ	0.02
Primary input (fist test)	Variable frequency sinusoid
Reference input (first test)	Additive white Gaussian noise, with zero mean and unit variance
Primary input (second test)	Malay utterance,Kosong,Satu,Dua... sampled at 8 kHz
Reference input (second test)	Machinery noise ,sampled at 8kHz
Performance measure method	Total mean square error MSE convergence

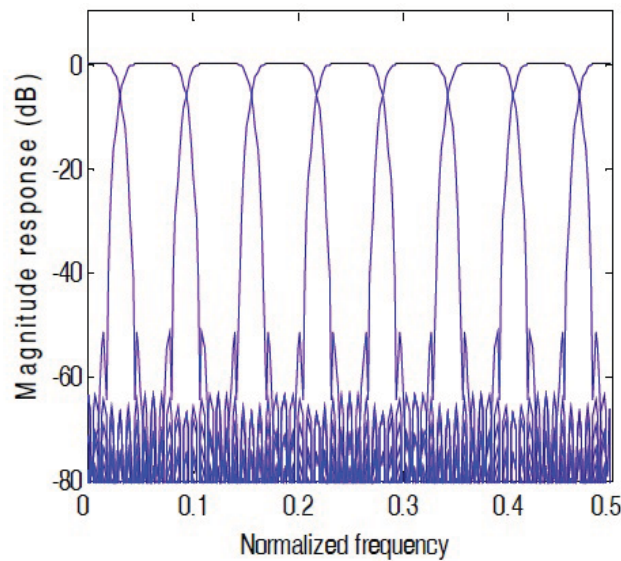


Fig. 5: Magnitude frequency response of DFT filter bank (even stacking)

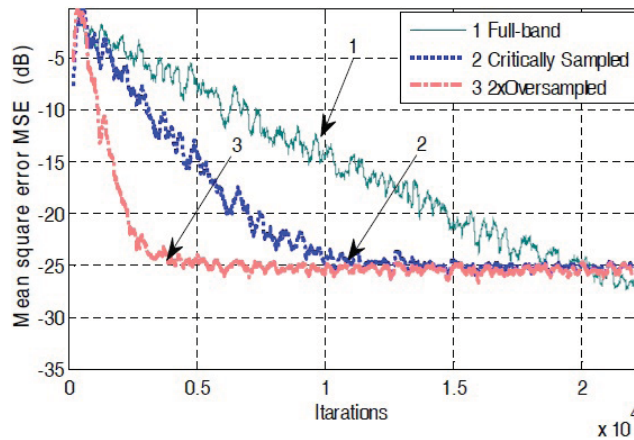


Fig. 6: Mean square error performance of the oversampled noise canceller compared to conventional fullband, and critically sampled systems, under white input.

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 Malay utterance “Kosong, Satu, Dua, Tiga” spoken by a woman as shown in Figure 7, this speech was sampled at 8 kHz. Machinery noise was used as a background interference to corrupt the above speech as shown in Figure 8. Mean square error plots are produced as shown in Figure 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, Figure 9 is reproduced as in Figure 10 with the plot of critically sampled system was dismissed since it is sufficient to compare with conventional fullband model.

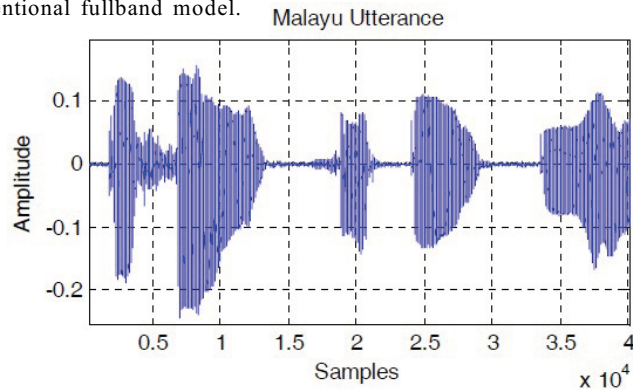


Fig. 7. Malay utterance “Kosong, Satu, Dua, Tiga” spoken by a woman

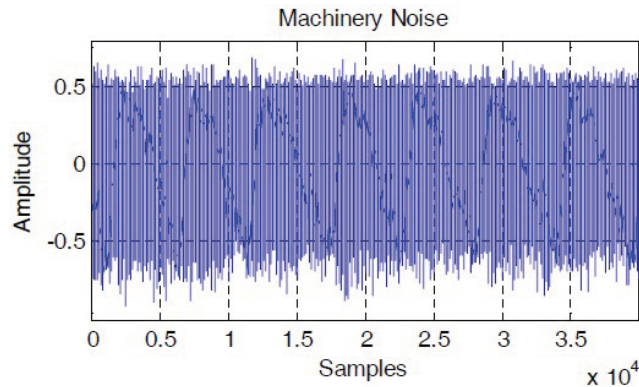


Fig. 8: Machinery noise as a background interference

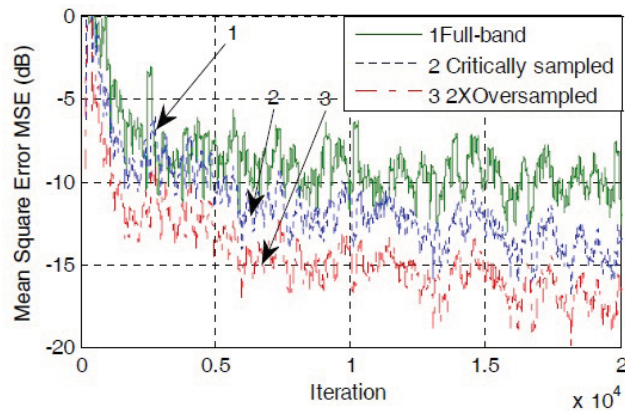


Fig. 9: MSE convergence under actual speech and background interference

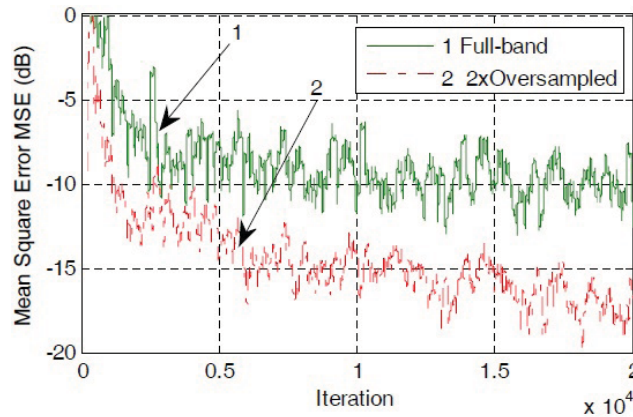


Fig. 10: MSE comparison of the two fold oversampled with a conventional full-band system.

The first advantage of these tests is the gain in computational efficiency. However, as the downsampling 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 subband decomposition of 16 band it is still less than the cost of conventional full-band system, as this is clear from Figure 4.

From Figure 6, it is clear that the mean square error MSE plot of the oversampled subband system converges faster than the critically sampled and fullband systems. While the fullband 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, Figure 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 fullband system cannot model properly with colored noise as the input to the adaptive filters, and the residual error can be severe 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 subband noise canceller does have better performance than the fullband system. It is evident from Figure 10 that the proposed system achieves 5 dB noise reductions better than the conventional single rate fullband system.

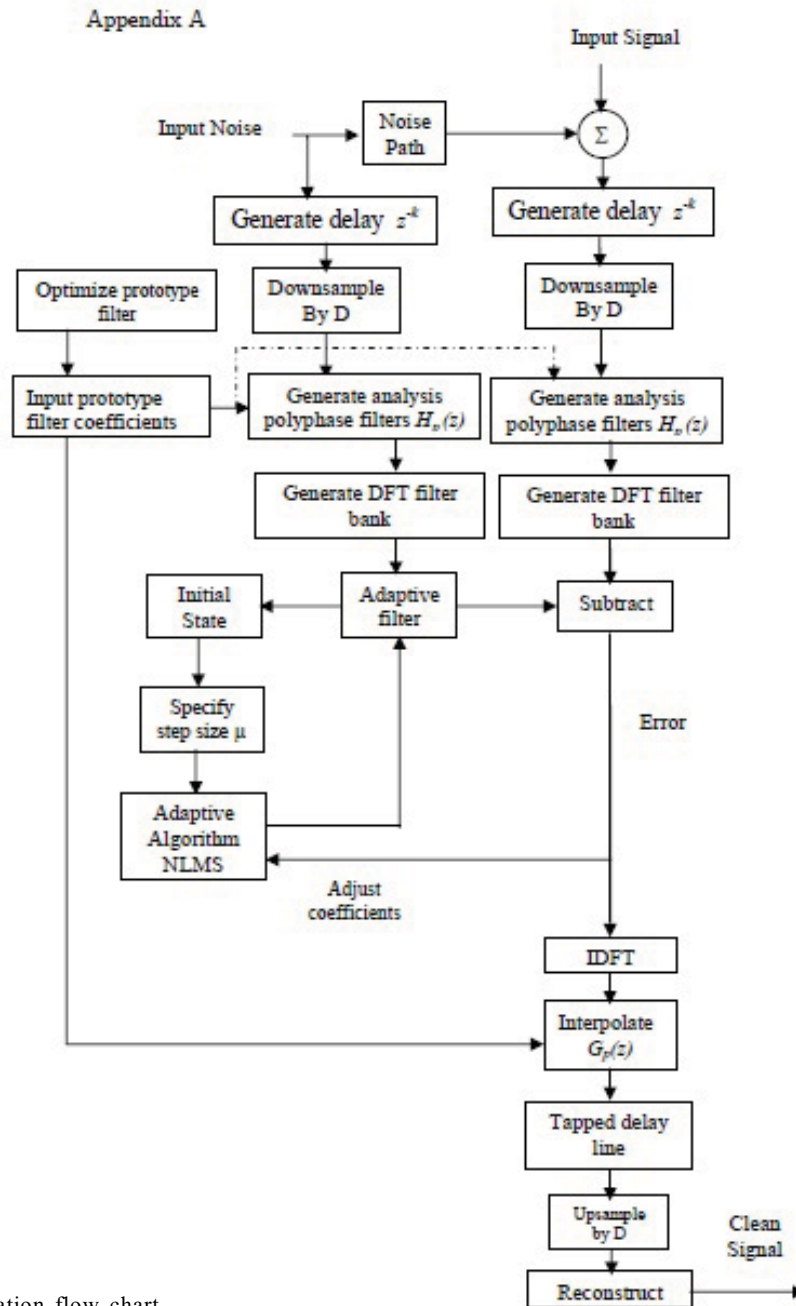


Fig. A: Simulation flow chart

Conclusions:

In this work, an oversampled subband 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 fullband 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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