International Journal of Current Engineering and Technology
E-ISSN 2277 – 4106, P-ISSN 2347 - 5161

Available at http://inpressco.com/category/ijcet

Review Article

Noise Cancellation using Adaptive Filtering: A Review

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Accepted 20 Sept 2014, Available online 01 Oct 2014, **Vol.4, No.5 (Oct 2014)**

Abstract

At the end of communication system information signal may be introduced with some noise along with the information signal. Noise may be additive or convoluted .Adaptive filter finds better solution to deal this problem. Use of Adaptive filter may filter out or suppressed noise from noisy signal getting the clean speech .This process is known as the adaptive noise cancellation. Subband adaptive filtering (SAF) finds better performance over a fullband adaptive filtering which employs multirate filter bank for signal decomposition and reconstruction. This technique allows for fast convergence and reduced computational complexity however insertion of filter bank introduced artifacts such as: aliasing, amplitude and phase distortion. This article deals with the review of various advancement in the adaptive algorithms made. Recently many methods have been proposed to reduce the effect of one or more artifacts. This article deals with the review of various advancement in this particular area of digital signal processing. Comparison tables of the main subband adaptive filtering are shown .The more effective comparison parameter of t these methods is Mean square Error (MSE) Plot.

Keywords: *Adaptive noise cancellation, Subband adaptive filtering (SAF), Mean square Error (MSE).*

1. Introduction

In practice the received speech signal contains some amount of noise component along with the information. The noise may be occurs due to coding of transmitted waveform (quantization noise) or an additive noise from background. Therefore for proper listing of this sound the noise need to be removed or suppressed form received noisy signal .The designing of such filter which removes or suppress noise required the signal and the noise be stationary that the statistics of both signals be known a priori. In practice, these conditions are rarely met.

Various signal processing techniques have been proposed over the years for noise reduction in the signals. There are two different approaches for electrical noise reduction. The first approach is passive electrical noise reduction techniques, such as those applied in hearing aids, cochlear implants, etc. where the signal and ambient noise are recorded using a microphone, noise reduction techniques such as spectral subtraction, the LMS algorithm, etc. are applied and the listener hears only the clean signal. One of the important assumptions of this technique is that the listener is acoustically isolated from the environment. This assumption is however not valid in a large particularly those number of situations where the ambient noise has very large amplitude. In such situations, the second approach of Active Noise Cancellation (ANC) is applicable. ANC refers to an electromechanical or electroacoustic technique of cancelling acoustic disturbance to yield a quieter environment. The basic principle of ANC is to introduce a cancelling “antinoise” signal that has the same amplitude but the exact opposite phase, thus resulting in an attenuated residual noise signal. ANC has been used in a number of applications such as hearing protectors, headsets, etc. The traditional wideband ANC algorithms work best in the lower frequency bands and their performance deteriorates rapidly as the bandwidth and the center frequency of the noise increases. Most noise sources tend to be broadband in nature and while a large portion of the energy is concentrated in the lower frequencies, they also tend to have significant high frequency components. Further, as the ANC system is combined with other communication and sound systems, it is necessary to have a frequency dependent noise cancellation system to avoid adversely affecting the desired signal.

The performance of any speech signal processing system is degraded in the presence of noise (either additive or convolution). This is due to the acoustic mismatch between the speech features used to train and test this system and the ability of the acoustic models to describe the corrupted speech (B. Widrow *et al*, 1975).

When processing the speech signal, the quality of speech may be at risk from various sources of interference or distortions. Typical sources of interference are:

• Background noise added to the speech signal: for example – environmental noise or engine noise when talking on a mobile phone,

• Acoustic or audio feedback: it occurs in two-way communication when the microphone in the telephone

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Captures the actual speech of another person and the speech of the first person reproduced from loudspeakers, and sends them both back to the first person,

• Amplifier noise: an amplifier can produce additional thermal noise, which becomes noticeable during significant signal amplifications,

• Quantization noise created in the transformation of the analogue signal to digital: the interference occurs during Sampling due to rounding up real values of the analogue signal,

• Loss of signal quality, caused by coding and speech compression.

2. Noise cancellation

Noise Cancellation is a variation of optimal filtering that involves producing an estimate of the noise by filtering the reference input and then subtracting this noise estimate from the primary input containing both signal and noise.

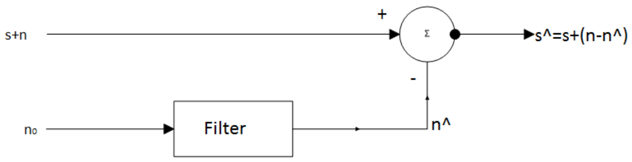

Fig.1 Noise cancelation

It makes use of an auxiliary or reference input which contains a correlated estimate of the noise to be cancelled. The reference can be obtained by placing one or more Sensors in the noise field where the signal is absent or its strength is weak enough. Subtracting noise from a received signal involves the risk of distorting the signal and if done improperly, it may lead to an increase in the noise level. This requires that the noise estimate nˆ should be an exact replica of n. If it were possible to know the relationship between n and nˆ, or the characteristics of the channels transmitting noise from the noise source to the primary and reference inputs are known, it would be possible to make nˆ a close estimate of n by designing a fixed filter. However, since the characteristics of the transmission paths are not known and are unpredictable, filtering and subtraction are controlled by an adaptive process. Hence an adaptive filter is used that is capable of adjusting its impulse response to minimize an error signal, which is dependent on the filter output.

3. Noise Cancellation Using Adaptive Filtering

A basic concept of Adaptive Noise Canceller (ANC) removes or suppresses the noise from a signal using adaptive filters. Adaptive filters are digital filters with an impulse response, or transfer-function that can be adjusted or changed over time to match desired system characteristics (Soni Changlani, *et al*, 2011); they require little or no a priori knowledge of the signal and noise characteristics. (If the signal is narrowband and noise broadband, which is usually the case, or vice versa, no a priori information is needed; otherwise they require a signal (desired response) that is correlated in some sense to the signal to be estimated.) Moreover adaptive filters have the capability of adaptively tracking the signal under non-stationary conditions.

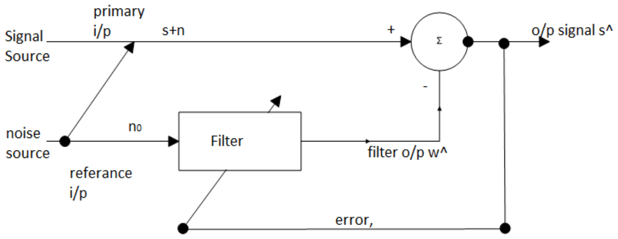

Fig.2 Adaptive Noise Canceller

The error signal to be used depends on the application. The criteria to be used may be the minimization of the mean square error, the temporal average of the least squares error etc. (Riitta Niemist and Ioan Tabu *et al*, 2001), Different algorithms are used for each of the minimization criteria e.g. the Least Mean Squares (LMS) algorithm, the Recursive Least Squares (RLS) algorithm etc. In the case of adaptive noise cancellation, we use the minimum mean-square error criterion. Examples of the adaptive filters are the Wiener filter, Recursive-Least-Square (RLS) algorithm, and the Kalman filters were proposed to achieve the best performance. Among them Least Mean Square (LMS) algorithm is most commonly used because of its robustness and simplicity, However the LMS algorithm suffers from significantly degraded performance for colored interfering signals due to the eigenvalue spread of the autocorrelation matrix of the input signal. In addition, as the length of the adaptive filter increases, the computational complexity increases. This can be a serious problem in acoustic applications such as echo and noise cancellation, where long adaptive filters are required to model the response of the noise path. This issue is of great importance in the hands-free application where processing power is kept low.

An alternative approach to reduce the computational complexity of long adaptive FIR filters is to incorporate block updating strategies and frequency domain adaptive filtering. These techniques reduce the computational complexity, because the filter output and the adaptive weights are computed only after a large block of data has been accumulated. However, the application of such approaches introduces degradation in the performance, including a substantial signal path delay corresponding to one block length, as well as a reduction in the stable range of the algorithm step size. Therefore for nonstationary signals, the tracking performance of the block algorithms generally becomes worse. (Ali O. Abid Noor 2011)As far as speed of convergence is concerned, it has been suggested to use the Recursive Least Square (RLS) algorithm to speed up the adaptive process. The convergence rate of the RLS algorithm is independent of the eigenvalue spread. Unfortunately, the drawbacks that is associated with RLS algorithm including its O (N2) computational requirements, which are still too high for many applications, where high speed is required, or when a large number of inexpensive units must be built. The Affine Projection Algorithm (APA) shows a better convergence behavior, but the computational complexity increases with the projection order in relation to LMS, where Projection denotes the order of the APA. As a result, adaptive filtering using subband processing becomes an attractive option for many adaptive systems to reduce these problems

4. Subband Adaptive Filtering in a Noise Cancellation Scenario

Subband adaptive filtering belongs to two fields of digital signal processing, namely, adaptive filtering and multirate signal processing. The basic idea of SAF is to use a set of parallel filters to divide the wideband signal input of the adaptive filter into narrower subband signals, each subband serving as an input to an independent adaptive filter. Subband decomposition greatly reduces the adaptive filter update rate through parallel processing of shorter filters.

Furthermore, subband signals are usually downsampled in a multirate system. This leads to a whitening of the input signals and therefore an improved convergence behavior of the adaptive filter system is expected. The subband decomposition is aimed to reduce the update rate, and the length of the adaptive filters, hopefully, resulting in a much lower computational complexity (Ali O. Abid Noor *et al*, 2011).

The conventional noise cancellation model is extended to a subband configuration by the insertion of sets of analysis and synthesis filters in signal paths, as depicted by Figure 2. Both input signals *s* and *n* are now fed into identical *M*-band analysis filter banks *H* (z), with nˆ being a filtered version of *n* by an unknown system *P(z).* Here, *P(z)* represents the acoustic noise path, *n* being correlated with and uncorrelated with *s*.

The ultimate goal is to suppress nˆ at the output *s* and to retain the non-distorted version of *s*. The update equation of the adaptive filter using the LMS algorithm is given by the following set of equation.

$$\hat{w}(m+1) = \hat{w}(m) + \mu . e(m) . n^*(m)$$

$$e(m) = v(m) - y(m)$$

$$y(m) = \hat{w}^T(\text{m}).\text{n (m)}$$

where *e(m)* represents the error signal, *y(m)* is the output of the adaptive filter, *w(m)* is the filter coefficient vector at the *mth* iteration, μ is the adaptation step-size factor m is a time index and $(.)T$ is the matrix transpose operator (Haykin, S *et al*, 2002).

This original model is extended to a subband configuration by the insertion of sets of analysis and synthesis filters in signal paths, as depicted by Figure 2. Both input signals *s* and *n* are now fed into identical *M*-band analysis filter banks *H* (z), with being a filtered version of *n* by an unknown system *P(z).* Here, *P(z)* represents the acoustic noise path, *n* being correlated with and uncorrelated with *s*. The ultimate goal is to suppress at the output *s* and to retain the non-distorted version of *s*.

After *D*-fold downsampling, adaptive filtering is performed in each subband separately. Updating of adaptive filter coefficients can be done with any kind of algorithm adaptation. However, for robustness and simplicity, the LMS algorithm is commonly used to update the subband filters *wk*ˆ In contrast to the traditional noise cancellation structure, in this setup, *P(z)* is estimated using a set of parallel, independently updated filters *wk* Outputs of the subband adaptive filters *yk* are subtracted from the subband desired signals *v* , forming the subband errors *e* . These errors are then upsampled and recombined in the synthesis filter bank *G* (z), leading to the clean output *s*. The input/output relationship can be expressed as:

$$\hat{S}_k(z) = \frac{1}{D} \sum_{k=0}^{m-1} G_k(k)\, U_k(z)$$

Where, $U_k(z) = E_k(z^D)$

There is Distortions due to the insertion of analysis and synthesis filter banks occurs which can be represented as,

$$\hat{S}_k(z) = A_0(z).S(z) + \sum_{i=0}^{D-1} A(i).S\left(ze^{-j2i\pi/M}\right)$$

Where,

$$A_0(z) = \frac{1}{M} \sum_{k=0}^{M-1} G_k(z).H_k(z)$$

$$A_i(z) = \frac{1}{D} \sum_{k=0}^{M-1} G_k(z).H_k(ze^{-2\pi i/D})$$

For *i=1, 2…D-1*. Here, A0(z) represents the total distortion transfer function of the filter bank for the non-aliased component of the system input *S*(z), while *Ai*(*z*) represents aliasing distortion and determines how well the aliased components of the system are attenuated.

The filter bank is the key tool in the design of subband adaptive filtering systems. Filter banks can be designed to be 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, thereby altering the perfect reconstruction property. There are tradeoffs in controlling the aliasing effect and the amplitude distortion level.

Depending on the value of the downsampling factor *D*, filter banks can be either critically sampled or oversampled. Filter bank can be critically sample or oversample .when downsapling factor is equal to number of channels i.e. (M=D) the system is critically sampled and when D<M the system is oversampled.

Computational savings are maximized when signals are critically downsampled However these systems require ideal filters in the analysis stage in order to avoid alising distortion on other hand oversampling has reduced aliasing distortion is trade off for extra computational cost.

5. Subband Adaptive Filtering Techniques

A. Critically Sampled

In The analysis of adaptive filtering algorithms found that critically sampled subband system cannot properly model the unknown system without the use of cross adaptive filters .However cross adaptive filter has two major disadvantages: slow convergence and extra computation (Gilloir, A. and M. Vetterli*et al*, 1992).

Another researcher (Yamada *et al*. 2004) proposed the use of frequency sampling filter (FSF) bank, this idea is based on the transformation of the subband signals into the frequency domain using discrete Fourier transforms (DFT), then choosing a number of frequency samples from each subband signal so that non-adjacent frequency bands have nulls at the center frequency of each subband. Thus subband adaptive filtering produced minimum alising distortion. Since the output is calculated only after accumulating a large block of data. In addition, a high computational burden is inevitable due to DFT calculations.

In an attempt to reduce computational expense (Naylor *et al*.1998) proposed a subband adaptive system using allpass polyphase infinite impulse response (IIR) filter banks. These IIR structures were introduced as an alternative to the standard approach involving finite impulse (FIR) filter banks. Such multirate systems with very high interband discrimination and low computational cost could be built using allpass polyphase structures. It was verified that adaptive filters in such systems perform as well as systems based on FIR filters. Spectral holes and signal delays are the main drawbacks associated with such an approach. These drawbacks are the adverse outcomes of adopting notch filters between subbands for the purpose of reducing aliasing. The use of IIR filter banks is also discussed by (Noor *et al*. 2010).

Another research, (Kim *et al*. 2008) has proposed a critically sampled structure to reduce aliasing effect. The inter-band aliasing in each subband is obtained by increasing the bandwidth of a linear-phase FIR analysis filter, and then subtracted from the subband signal. This aliasing reduction technique introduces spectral dips in the subband signals. Therefore, extra filtering operation is required to reduce these dips (Gilloir and Vetterli *et al*. 1992). Oversampled schemes have been suggested as the most appropriate solution to avoid aliasing distortion associated with the use of critically sampled filter banks.This was originally recommended by Gilloire and Vitterli .The small eigenvalues are generated by the roll-off of the subband input power spectrum. It was later demonstrated by the same authors that this problem could be mitigated by the use of increased bandwidth analysis filters (DeLeoAnd Etter 1995).Effectively the amplitude distortion, if the filters constituting the filter bank were constrained to be linear phase FIR filters. Using amplitude distortion as a criterion to minimize aliasing by a nonlinear optimization procedure, it was found that the best prototype filter is the one designed using Kaiser or Dolph-Chebychev windows Optimization techniques have also been discussed by Noor *et al*. (2011). An optimized 2-fold oversampled *M*-band noise cancellation technique is used to mitigate the problem of aliasing insertion associated with critically sampled schemes. Variable step size version of the LMS algorithm is used to control the noise in the individual branches of the proposed canceller. The system is implemented efficiently using polyphase format and FFT/IFFT transforms. The proposed scheme offers a simplified structure that without employing cross-filters or gap filter banks reduces the aliasing level in the subbands. The performance under white and colored environments is evaluated and compared to the conventional fullband method as well as to a critically sampled technique developed by (Kim *et al*. 2008). This evaluation is offered in terms of MSE convergence of the noise cancellation system.

Table 1 Comparison of literature proposal for Critical Sampling

Source	Convergence rate	Computational Complexity
Gilloire and Vitterli	Slower	N/M
Yamada	No Comparison found	Approximately 6N
Deleon and Etter	Faster	2N/M
Naylor	Faster	N/M
Kim	Comparable Under white noise	2N/M+2(L'+)+3(Lω +1)+LFB +3$log_2 M$

B.Oversampled Structures

(DeLeon and Etter *et al*. 1995) verified that in spite of the increase in computational load, oversampled systems are still more efficient than the equivalent fullband ones for a certain number of subbands. (sridharan *et al*.1998) has also developed an oversampled technique for adaptive filtering purposes. Sridharan's study targeted issues both of complexity and convergence; the computational complexity was reduced to a half of the fullband system. This was achieved by restricting non-adjacent filters of a perfect reconstruction filter bank (PRFB) to be non-overlapping. In Sridharan's method, it is not clear whether the system will give a satisfactory convergence for colored input signals or not.

In a related study, (Chin and Boroujeny *et al*.2001) have suggested the use of real-valued subband signals instead of the conventional complex-valued types, proposing a subband adaptive filter structure using an SSB-modulated filter bank.

Table 2 Comparison of oversample structures

Source	Convergence rate	Computation
DeLeon and Etter	Initially faster ,slower on steady state	2N/M
Sridharan	Faster compared to standerd	2N/M
Chin an Boroujeny	Faster	2N/M+real Value

The resulting subband signals are real-valued, thus eliminating the need to deal with complex-valued signals as in the case of conventional subband adaptive filters. The resulting subband adaptive filter has performance comparable to its complex-valued counterpart in terms of delay, convergence and distortion. However, the technique poses a potential increase in the computational complexity

Table 3 Comparison of Delayless subband adaptive filtering

Algorithm	Number of real Multiplication
Proposed UDFT	$4log_2M$
PFFT-2	$\frac{8N}{M}\left[2+\frac{4}{M}\right](log_2\frac{8N}{M})+log_2 2N$

Table 4 Tabular Comparison on Some Surveyed Literatures

Author	Research	Description
Boll, S.	Suppression of acoustic noise in speech using two microphone adaptive noise cancellation	In this paper a novel method for cancellation of broadband/narrowband noise from speech signals is proposed. Independent component analysis (ICA) and wavelet packet approaches have been combined for blind noise separation from Mixtures of speech signals. ICA method is used to estimate matrix A, which defines how the mixture signals have been mixed. Wavelet packets are used for de-correlation of approximation of noise and speech.
Darlington, D.J.	Sub-band, dual-channel adaptive noise cancellation using normalised LMS	An adaptive noise cancellation scheme for speech processing is described. Adaptive filters are implemented in sub-bands, based on a model of the human cochlea. A modification to the LMS structure is introduced which guarantees stability and convergence. This modification, a non-recursive normalisation, is used both in a wideband and in a sub-band implementation of the scheme. The effect of this normalisation is to cause the speech to be distorted, indicating that there is little benefit in using normalised LMS in a sub-band scheme, whether the application uses classical or intermittent noise cancellation
Ali A. Milani	A New Delayless Subband Adaptive Filtering Algorithm for Active Noise Control Systems	Acoustic paths such as those encountered in ANC application usually have long impulse responses, which require longer adaptive filters for noise cancellation. Subband adaptive filters working with a large number of subbands have been shown to be a good solution to this problem. The focus of this paper was to design such a high-performance SAF algorithm. The performance limiting factors of existing SAF structures were found to be due to the inherent delay and side-lobes of the prototype filter in the analysis filter banks. Hence, the analysis filter banks were modified to reduce the inherent delay. A new weight stacking transform was designed to alleviate the interference introduced by the side-lobes.
Ali O. Abid Noor,	Adaptive Filtering Using Subband Processing: Application to Background Noise Cancellation	Adaptive filter noise cancellation systems using subband processing are developed and tested in this chapter. Convergence and computational advantages are expected from using such a technique. Results obtained showed that; noise cancellation techniques using Critically sampled filter banks have no convergence improvement, except for the case of two-band QMF decomposition, where the success was only moderate. Only computational advantages may be obtained in this case. An improved convergence behavior is obtained by using two-fold oversampled DFT filter bank that is optimized for low amplitude distortion.
Riitta Niemist¨o2	Signal Adaptive Subband Decomposition for Adaptive Noise Cancellation	A new architecture for adaptive noise cancellation where the signals involved are first decomposed in two subbands and adaptive filtering is performed separately for each subband signal. When the subband decomposition is performed such that the analysis filters compacts most of noise power in one subband and leaves almost no noise power in the other band, the adaptive filtering turns out to be more efficient than in the single channel case.

of the system due to the increased number of subbands (Noor *et al*. 2011). They have optimized a Hamming window base analysis/synthesis to achieve a good convergence behavior at moderate computational costs.

The advantages of subband adaptive filtering systems have been widely acknowledged. Although the gain in computational complexity is clearly advantageous in long acoustic environments, the use of SAF may be impractical in the presence of high levels of distortion brought about by the insertion of filter banks. Filter banks introduce three types of artifacts: aliasing, amplitude and phase distortions. Another disadvantage of using SAF is the extra processing delay, which may rule out the use of these systems for real-time implementations

C. Delayless Subband Schemes

The conventional approach to subband adaptive filtering is ruled out for many applications because delays are introduced into the signal path. Delayless subband adaptive filtering schemes have been proposed in the literature to circumvent this problem. A delayless structure in a noise cancellation setup is shown in Figure 7. The pioneering work involving this type of schemes was performed by Morgan and Thi *et al*. (1995). They have presented a new class of subband adaptive filter architecture in which the adaptive weights adaptive filter architecture in which the adaptive weights transformed into an equivalent set of wideband filter coefficients. In this manner, signal path delay is avoided while retaining the computational and convergence speed advantages of subband processing. An additional benefit is accrued through a significant reduction of aliasing effects. More efficient subband filters can be designed by relaxing the low stopband response necessary to control aliasing. The delayless structure is very similar to the frequency domain structure proposed earlier by Shynk *et al*.(1992), i.e., the adaptive weights are computed for each subband's FFT bins separately and then transmitted to an equivalent wideband filter.

However, it differs from the frequency domain structure in that the actual processing of the subband signal takes place in the time domain. Subband adaptive filters working with a large number of subbands has been proposed by The ali milani *et al*. (2009)in their The performance limiting factors of existing SAF structures were found to be due to the inherent delay and side-lobes of the prototype filter in the analysis filter banks. Hence, the analysis filter banks were modified to reduce the inherent delay. A new weight stacking transform was designed to alleviate the interference introduced by the side-lobes.

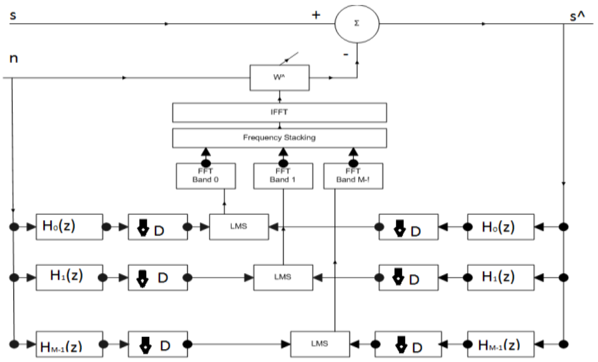

Fig.3 Delayless subband adaptive filtering configuration

Conclusion

The performance of any speech signal processing system is degraded in the presence of noise (either additive or Convolution). This is due to the acoustic mismatch between the speech features used to train and test this system and the ability of the acoustic models to describe the corrupted speech. Various techniques for filtering the noise from a speech waveform have been studied. LMS algorithm operating in fullband suffers from significantly degraded performance for colored interfering signals however this effect can be minimize with use of subband processing.

The Depending upon the value of Downsampling rate and number of subband the SAF (Subband adaptive Filtering) is divided as critically sampled ad Oversampled. Standard critically-sampled systems offer optimum computational savings. Unfortunately, these systems cannot properly model unknown systems and also require cross-adaptive filters to correctly model the systems. This leads to slow convergence and additional computational costs. Employing infinite impulse response IIR filter banks offers the best solution in terms of convergence and computational costs. Oversampled structures have mitigated the problem of aliasing in critically sampled systems. This comes at the expense of higher computational costs. As a result, increased bandwidth analysis filters have been proposed to solve this problem.

Delayless proposals have addressed the input-output delay while retaining convergence and complexity issues as advantages of subband decomposition. The computational requirements of such structures are still too high for many applications, where high speed is required, or when a large number of inexpensive units must be built. In applications such as speech and audio, highly selective filter banks are necessary.

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