World Applied Sciences Journal 21 (1): 113-124, 2013
ISSN 1818-4952

DOI: 10.5829/idosi.wasj.2013.21.1.2436

A Review of Advances in Subband Adaptive Filtering

Ali O. Abid Noor, Salina Abdul Samad and Aini Hussain

Department of Electrical, Electronics and Systems Engineering,
Faculty of Engineering and Built Environment,
Universiti Kebangsaan Malaysia, UKM, 43600 Bangi, Selangor, Malaysia

Abstract: Subband adaptive filtering (SAF) generally employs multirate filter banks for signal decomposition and reconstruction. This technique allows for fast convergence and reduced computational complexity through use of the robust least mean squares (LMS) algorithm in acoustic environments. However, the performance of subband adaptive schemes is often degraded by artifacts introduced by the insertion of filter banks in the signal path. Recently, several schemes have been proposed to reduce the effect of one or more of these artifacts. This article presents an overview of the development and trends in this particular area of digital signal processing. Comparison tables are given to assess the performance of the main subband adaptive structures found in literature. It also presents simulation results obtained from some cases of adaptive noise cancellation configurations as examples of these SAF systems. The effect of aliasing insertion is demonstrated for various settings of filterbanks and the influence of filter bank optimization on the performance is depicted as mean square error (MSE) plots.

Key words: Adaptive Filtering · Filter Banks · Subband Processing · Noise Cancellation

INTRODUCTION

Adaptive filters play important roles in many signal processing systems. In this context, the least mean squares (LMS) adaptive filtering algorithm has been used extensively due 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 [1]. 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. These issues are especially important in hands-free communications, where processing power must be kept as low as possible [2]. Therefore, subband adaptive filtering (SAF) becomes an attractive option to reduce these problems. 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. 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. In addition, improved performance can be obtained using this technique, owing to the fact that the subband inputs are now whiter than the original wideband input. This article presents an overview of the techniques of subband adaptive filtering, which allow adaptive filtering to reap some of the benefits of subband decomposition of the input signals.

Subband Adaptive Filtering in a Noise Cancellation Scenario: The conventional noise cancellation model is shown in Figure 1, where the noisy signal s is fed through

Corresponding Author: Ali O. Abid Noor, Department of Electrical, Electronics and Systems Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, UKM, 43600 Bangi, Selangor, Malaysia.

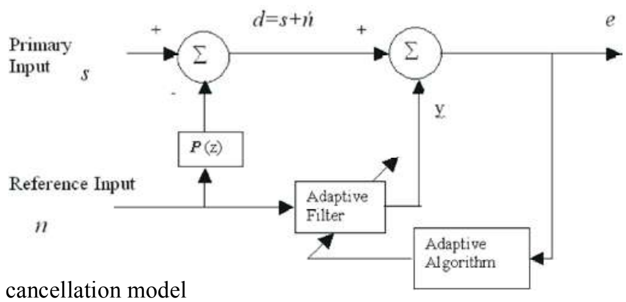

Fig. 1: Conventional noise cancellation model

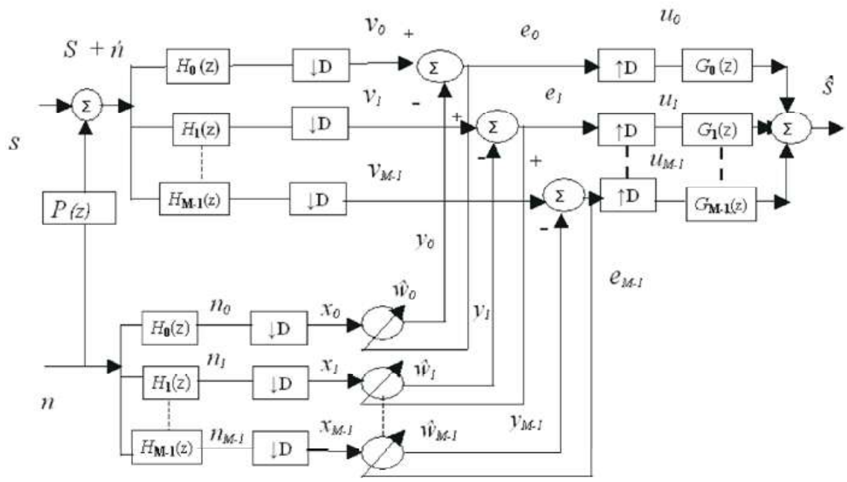

Fig. 2: Subband noise cancellation configuration

a primary input, while noise n provides the reference input to the model. $ń$ is added to s through a path $P(z)$ producing the desired signal d, where the error signal e should ideally be equal to s when steady state is reached. The adaptive filter attempts to model the path response $P(z)$, hence producing replicas of the noise that has corrupted the signal s. The update equations of the adaptive filter using the LMS algorithm are given by the following set of equations [3].

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

$$e(m) = v(m) - y(m) \tag{2}$$

$$y\ (m) = \hat{\mathbf{w}}^T(m)\mathbf{n}(m) \tag{3}$$

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.

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 $H_k(z)$, with $ń$ being a filtered version of n by an unknown system $P(z)$. Here, $P(z)$ represents the acoustic noise path, n being correlated with $ń$ and uncorrelated with s. The ultimate goal is to suppress $ń$ 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 w_k. In contrast to the traditional noise cancellation structure, in this setup, $P(z)$ is estimated using a set of parallel, independently updated filters w_k. Outputs of the subband adaptive filters y_k are subtracted from the subband desired signals v_k, forming the subband errors e_k. These errors are then upsampled and recombined in the synthesis filter bank $G_k(z)$, leading to the clean output s. The input/output relationship can be expressed as:

$$\hat{S}_k(z) = \frac{1}{D}\sum_{k=0}^{M-1} G_K(z)U_k(z) \tag{4}$$

where

$$U_k(z) = E_K(z^D) \quad (5)$$

Distortions due to the insertion of analysis and synthesis filter banks can be expressed within the following input-output relationship:

$$\hat{S}_k(z) = A_0(z)S(z) + \sum_{i=0}^{D-1} A_i(z)S(ze^{-j2i\pi/M}) \quad (6)$$

where

$$A_0(z) = \frac{1}{M}\sum_{k=0}^{M-1} G_K(z)H_k(z) \quad (7)$$

$$A_i(z) = \frac{1}{D}\sum_{k=0}^{M-1} G_K(z)H_k(ze^{-2\pi i/D}) \quad (8)$$

for $i=1,2,\ldots D-1$. Here, $A_0(z)$ represents the total distortion transfer function of the filter bank for the non-aliased component of the system input S(z), while $A_i(z)$ 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. Computational savings are maximized when signals are critically downsampled, i.e., $M=D$. However, these systems require ideal filters in the analysis stage in order to avoid aliasing distortion. On the other hand, the use of a downsampling factor that is less than the number of channels, i.e., oversampling, has the advantage of permitting moderate order filters to be used as well as reducing the aliasing distortion of the subband system. In oversampled subband adaptive systems, reduced aliasing distortion is the trade-off for extra computational costs. The rest of this paper is arranged as follows: sections 3 and 4 review systems according to the type of downsampling used in the analysis/synthesis filter banks. In section 5, another class of subband adaptive filtering, known as delayless subband adaptive filtering, is reviewed and finally, section 6 presents concluding remarks.

Critically Sampled Subband Systems: Perhaps, the earliest proposal dealing with subband adaptive filtering can be found in the work by Gilloire and Vitterli [4], where the desired signal and the reference signals were divided into subbands using identical filter banks and each subband was then processed independently. It was demonstrated by these authors that critically sampled subband systems cannot properly model the unknown system without the use of cross adaptive filters. This is due to the presence of aliasing distortion, which resulted from the downsampling process. Cross adaptive filters were suggested as remedy for this problem. However, the use of cross adaptive filters has two major disadvantages: systems with adaptive cross filters generally converge slowly and they also impose extra computational costs. In a separate work, Yamada *et al*. [5] avoided the use of cross adaptive filters, they proposed the use of a frequency sampling filter (FSF) bank. Their 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. In this way, SAF is expected performed with minimum aliasing distortion. The method has a structure similar to frequency domain adaptive filtering; it consists of block updating DFTs, which has poor tracking capability for non-stationary signals, 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 another study, it has been shown by Usevitch and Orchard [6] that SAF is a generalization of transform domain adaptive filters based on structural subband decompositions. Usevitch and Orchard gave the name of filter bank adaptive filters (FBAFs) to the structure. They derived a parameterization for a class of finite impulse response (FIR) perfect reconstruction filter banks, which was used to design FBAFs having optimal error performance, provided that prior knowledge of the application was available. The mean squared error convergence plots presented in the FBAF system deliver no substantial improvement in the convergence behavior over conventional fullband schemes. Similar to the technique found in [5], this method belongs to block updating strategies, which produce poor tracking behavior. The conditions for the filter bank were also researched by Petraglia *et al*. [7]. It is shown that increasing filter bank order will improve convergence behavior of the critically sampled subband systems for colored inputs without the use of cross adaptive filters. Howevwr, the computational complexity was higher than that of a standard subband scheme. A standard subband scheme is the one proposed by Gilloire and Vitterli [4], without the use of cross filters. To improve the convergence performance of SAF systems, a polyphase structure is offered by Pradhan and Reddy [8]. They showed that the convergence rate of the SAF could improve considerably with an increasing number of subbands. A weighted cost function is used in this approach. Cross filters are avoided and the adaptive filters in the subbands are independent of the analysis and synthesis filters. The overall computational complexity of this approach is nearly the same as that of a fullband adaptive filter. This latter result is contradictory to one of the main objectives of adopting subband adaptive filtering. However, if implementation cost is not an issue, this approach may be an excellent one for controlling highly colored interference in audio applications.

In an attempt to reduce computational expense, Naylor *et al*. [9] 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. It has been shown by Naylor *et al*. [9] that 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*. [43], where IIR filter banks are used in the analysis stage and the synthesis filter bank is designed to compensate for the phase distortion. The method gave good convergence behavior without any equalization stage that would increase processing delay to non-tolerable level.

A study of the application of high-order adaptive filters to the problem of acoustical echo cancellation has been conducted by Breining *et al*. [10]. The study introduced subband adaptive filtering as a method for reducing computational complexity, which would allow implementations using low cost, fixed-point digital signal processors. An additional degree of freedom in system design is provided, in a sense that all necessary forms of control and detection operate independentlyperformed in each channel, which could increase the speed of convergence. The price to be paid for these advantages is a significant delay introduced into the signal path.

Based on the work in [8], Choiand and Bae [11] have proposed a subband affine projection (AP) algorithm originating from the fullband affine projection algorithm originally proposed by Ozeki and Umeda [12] for acoustic echo cancellation. The algorithm uses orthogonal subband filters (OSF) as the alternative method for whitening the highly correlated inputs. By combining the merits of the OSFs and the AP algorithm, a method with a fast convergence rate and reduced computational complexity was derived. The subband AP algorithm could be reduced to a simplified form such as the NLMS by partitioning over the number of subbands as the projection order.

Subband adaptive filtering has also been used to reduce acoustic echoes in loudspeaker-enclosure-microphone (LEM) systems [13]. In this LEM acoustic echo canceller system, a fixed filter is used to remove a major portion of the echo, while the adaptive filter deals with the residual echo due to the perturbed echo path. The efficiency and performance are maximized by using the subband structure in which a different length and step size of the filter may be used independently for each sub-band. Cosine-modulated analysis and synthesis filter banks are used for signal splitting and reconstruction in the LEM system. The treatment of aliasing and other artifacts due to filter banks was not discussed in [13]. Furthermore, additional computational costs are required, compared to the standard subband system, due to the introduction of a fixed filter in each subband.

To improve the convergence rate of the NLMS algorithm, a multiple-constraint optimization criterion for the SAF has been proposed by Lee and Wang [14]. It was shown that, the proposed normalized SAF algorithm derived from this criterion exhibits faster convergence under colored excitation compared to the fullband NLMS algorithm. Regarding computational complexity, the NSAF and NLMS algorithms require almost the same number of multiplications per sampling period, which is still too high for real-time implementation. However, the NSAF method showed an improved performance under colored environments. The issue of improving the convergence rate in colored conditions was also addressed by Petraglia and Batalheiro [15], through the use of non-uniform subband adaptive systems with critical sampling. However, computational complexity and delay constraints were not addressed.

In order to fully exploit the benefits of SAF, Kim *et al.* [16] proposed a structure with critical sampling. The focus was the elimination of aliasing distortion. The interband aliasing is extracted in each subband using the bandwidth-increased FIR linear-phase analysis filters and then subtracted from each subband signal. However, the use of the bandwidth-increased analysis filters introduces an extra computational load and the almost alias-free subband signals have spectral dips. These spectral dips are reduced using a filter for the spectral flatness and then the outputs are used for adaptive filtering in each subband. The computational complexity of Kim's algorithm is reduced by approximately the number of subbands, compared to that of the fullband algorithm. Kim's structure has a similar convergence rate as the fullband structure for white noise input and a better convergence rate than both the equivalent fullband and the conventional SAF structures under colored input.

Based on the work in [6], Petraglia and Batalheiro [17] have studied the design of optimal filter banks for subband adaptive filtering with critical sampling. The focus was on minimizing the mean squared error and to achieve faster convergence in subband adaptive systems. Such a filter bank design method is based on a theoretical analysis of the convergence properties of the adaptation algorithm and uses a nonlinear optimization routine. It is observed that the convergence rate can be increased by increasing the number of bands, provided that the order of the prototype filter is increased, thus increasing the total computational complexity and the total system delay.

A new version of subband NLMS has been introduced by Abadi [18] recently. This version is based on a variant of proportionate normalized least mean squares (PNLMS). The PNLMS was previously introduced by Duttweiler [19] as a fast-converging alternative to the NLMS algorithm in today's echo cancellers. In the PNLMS algorithm, the adaptation gain at each tap position varies from position to position and is roughly proportional at each tap position to the absolute value of the current tap weight estimate. The total adaptation gain being distributed over the taps is monitored and controlled so as to keep adaptation quality (known as the misadjustment noise) constant. Following this, a combination of the NLMS and PNLMS adaptive filtering algorithms has been proposed by Nekuii and Atarodi [20] as a further improvement to the convergence of the PNLMS in network echo cancellers. Furthermore, Khong *et al.* [21] exploited both the fast convergence of the improved proportionate normalized least mean squares (IPNLMS) algorithm and the efficient implementation of multi-delay adaptive filtering (MDF) for a sparse system identification algorithm in network echo cancellation, thus inheriting the beneficial properties of both algorithms. The proportionate normalized subband adaptive filter algorithms proposed by Abadi [18] exhibited improved convergence speed compared with the ordinary NSAF algorithm for sparse system identification, at the expense of a moderate increase in the computational complexity.

An approximate expression that describes the convergence behavior of the cancellation error of the critically sampled subband adaptive filter ADF was formulated by Ohno and Sakai [22]. From this expression, the convergence speed of the subband ADF is investigated. Based on the analysis of this expression, it is concluded that the critically sampled subband adaptive filter does not always have advantages over the fullband adaptive filter in terms of convergence speed.

Table 1 shows a comparison summary of the different techniques found in the literature for SAF systems with critical sampling. In this table, convergence speed and computational complexity are the main parameters used in the assessment. These parameters are compared to the conventional fullband adaptive filtering scheme. Adaptive filter length is referred to as *N*, while the letter *M* represents the number of subbands. Assuming that a very long impulse response is to be identified, such as that found in acoustic environments, the bulk of the computational load is concentrated in the adaptive section. In this paper, the subband noise cancellation system shown in Figure 2 is simulated for different combinations of subbands number and analysis/synthesis filters tap-lengths. The effect of increasing the number of subbands and filter order on the amount of aliasing insertion in critically sampled systems is shown in Figure 3. Mean square error convergence plots are shown in Figure 4 to demonstrate the effect of increasing the number of subbands on the convergence behaviors of the noise cancellation system described in section 2.

Oversampled Structures: 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 [4] as a way to avoid using cross adaptive filtering. DeLeon and Etter [23] have carried out several experiments on subband adaptive filtering using oversampled filter banks. It has been verified that in spite of the increase in computational load, oversampled

Table 1: A summary comparison of selected literature proposals for critical sampling case

Source	Convergence rate	Computational complexity	Comments
Gilloire and Vitterli [4]	Slower	N/M	Cross terms needed, at extra cost
Yamada *et al.* [5]	No comparison found	Approximately 6N	Poor tracking for non stationary signals
Petraglia *et al.* [7]	Initially faster	3N/M	High residual noise
Pradhan and Reddy [8]	Faster	$C_T = 3N + 2M(L + 2)$	Excellent for highly colored noise
Naylor *et al.* [9]	Faster	N/M	Signal delay plus spectral holes
Breining *et al.* [10]	Faster	2N/M	Suitable for fixed point implementation
Choi and and Bae [11]	Faster	N/M for low order projections. For high order projections $= P^3/(2M^3)$ $+ NP^2(M+1)/M^3$ $+NP(P + M + 1)/M^2$ $+ 2ML$ where P is the order of the projection.+2	Complexity increases substantially with projection order
Bai *et al.* [13]	Faster	N/M+ extra costs due to fixed filters	Aliasing distortion not discussed
Lee and Wang [14]	Faster	Almost the same as fullband, N	High complexity for real time
Petraglia and Batalheiro [15]	Faster	Not discussed	Good colored noise performance
Kim *et al.* [16]	Comparable under white noise	$\frac{2N}{M} + 2(L'+1) + 3(L_\omega + 1) + L_{FB} + 3\log_2 M$ where L' is the increased bandwidth filter length, L_ω is the order of the filter for flattening the spectrum and L_{FB} is the prototype filter of the filter bank used in the system.	Good only for colored environments
Petraglia and Batalheiro [17]	Faster	3N/M	Potential increase in the computational complexity
Abadi [18]	Improved compared to conventional SAF	N/M + extra PLNMS cost	Improvements only in initial convergence

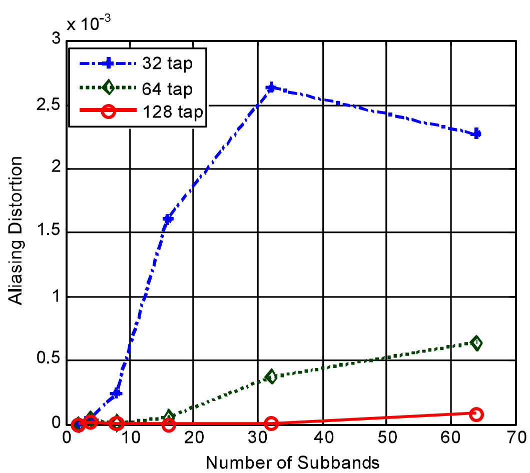

Fig. 3: Aliasing distortions against the number of subbands for different FIR prototype filter length

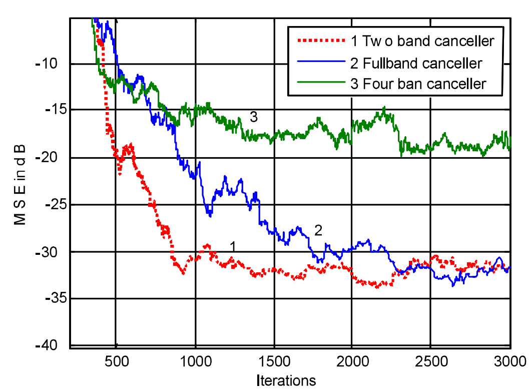

Fig. 4: MSE performance of subband noise canceller compared to fullband under white noise input

systems are still more efficient than the equivalent fullband ones for a certain number of subbands. However, these systems suffer from slow asymptotic convergence. It is demonstrated by Leon and Etter [23] that oversampled filter banks themselves color the input signal, which leads to a slow convergence. These problems are traced back to the fact that oversampled subband inputs will likely generate an ill-conditioned correlation matrix. In this case, 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 [24]. In this technique, the analysis filter magnitude frequency responses are extended beyond the required cut-off, so that the synthesis filters can shave off the distorted components near the band edges. This way, a better modeling behavior was obtained for a room impulse response in acoustic echo cancellers. In another work, Harteneck *et al*. [25] proposed a different oversampled structure that could reduce band edges distortion without the use of cross adaptive filters. The architecture uses real-valued oversampled filter banks with different downsampling ratios in each subband. The prototype analysis and synthesis filters were designed with an iterative least squares algorithm that minimizes a certain performance criterion, which in turn reduces the inband aliasing. It was shown that a lower computational complexity could be obtained compared to a fullband implementation using lower-order adaptive filters at lower sampling frequencies.

Sridharan [26] 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 fullnad system. This was achieved by restricting non-adjacent filters of a perfect reconstruction filter bank (PRFB) to be non-overlapping. The channel filters of Sridharan's structure are related to the modeling system through the PRFB filters. The subband adaptive filtering algorithm was developed by making channel filters adaptive. Cross filters were derived from the main channel filters. In Sridharan's method, it is not clear whether the system will give a satisfactory convergence for colored input signals or not. In a further study by Harteneck *et al*. [27] on subband adaptive filtering with oversampled structures, a design algorithm for real-valued and complex-valued oversampled filter banks is developed, with the main of reducing the inband aliasing. Although the computational complexity of the adaptive section was greatly reduced compared to the fullband adaptive filter, the total computational complexity of the oversampled subband adaptive filter is still influenced by the complexity of the filter banks used in the configuration.

In a related study, Chin and Boroujeny [28] 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. 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 of the system due to the increased number of subbands.

Petraglia and Piber [29] followed a similar procedure to that proposed by DeLeon and Etter [24] to increase the convergence rate of the subband adaptive filter. The synthesis filters in were optimized to give even better results in terms of mean squared error performance. Oversampled filter banks have been developed also developed with the purpose of reducing aliasing distortion as well as total filter bank distortion [30], 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*. [44]. They have optimized a Hamming window base analysis/synthesis to achieve a good convergence behavior at moderate computational costs.

Table 2 presents a comparison summary of the various oversamplled SAF systems. The assessment is based on convergence and complexity, compared to the full band scheme, with the same parameters and assumptions as in Table 1. While, Figure 5 shows the effect of increasing the number of subbands on the total computational complexity of oversampled systems compared to critically sampled structures. Figure 6 presents simulation results obtained from optimization of filter banks in oversampled noise cancellation systems. Here, the same structure as that described in Figure 2 is used, with the downnsampling factor D is set to twice the number of subbands M. In this case, D was set to eight, while M equals to four. The filter bank prototype filter is designed using Hamming window technique with order of 128.

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 [31]. They have presented a new class of subband adaptive filter architecture in which the adaptive weights

Table 2: A summary comparison of oversampled structures

Source	Convergence rate	Computational complexity	Comments
DeLeon and Etter [23] in steady state	Initially faster, slower on steady state	2N/M	High residual noise
DeLeon and Etter [24]	Faster	2N/M	Residual noise performance is same as fullband
Harteneck *et al.* [25]	Faster	Approximately N/ 2.7 for LMS type in the best case	Suitable for colored environment
Sridharan [26]	Faster compared to standard subband scheme	2N/M	No comparison with fullband found
Harteneck *et al.* [27]	Faster for colored noise	28% N for real valued 7.4%N for complex valued	Performance limited by the amount of inband aliasing and reconstruction error
Chin and Boroujeny [28]	Faster	2N/M+ real valued calculation costs	Complexity depends on filter bank order

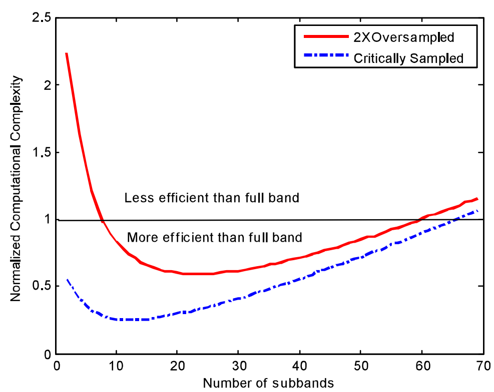

Fig. 5: Computational complexity analysis of the oversampled subband noise canceller for a fixed FIR filter order

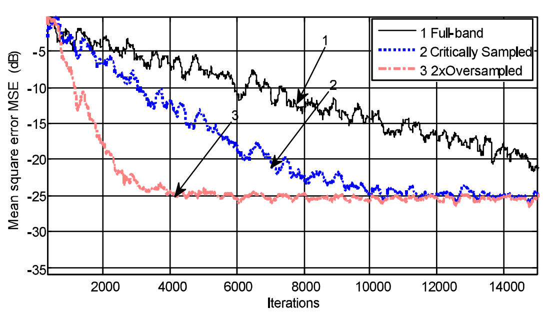

Fig. 6: Convergence behaviour of optimized oversample noise canceller

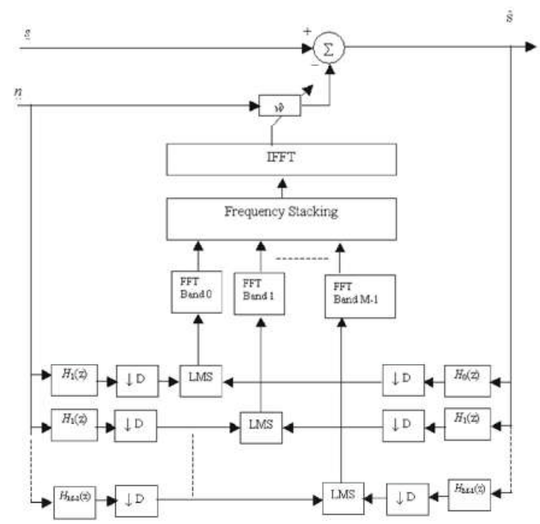

Fig. 7: Delayless subband adaptive filtering configuration

are computed in subbands but are then collectively 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 [32], 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. This technique is computationally intensive, as it requires performing a polyphase FFT of the error and filtered reference signals as well as an inverse FFT of the filter weights. However, it is still less intensive than an equivalent wideband adaptive filter.

Another study addressing the delay issue is the work by Boroujeny and Wang [33], where subband structures have been investigated from a delay point of view. Boroujeny and Wang followed a different strategy from that of [31]. A design technique was offered that followed the idea of eigenfilters, as proposed by Vaidyanathan and Nguyen [34]. The low-delay design could reduce the delay significantly. For a similar performance compared to the subband scheme, the delay was reduced by more than 50%. This was achieved at the cost of an increase in the order of the analysis and synthesis filters, which, of course, increases the memory requirement of the system as well as its computational complexity.

In a different work, Merched *et al*. [35] followed the same idea as Morgan and Thi [31], but in this case, the wideband signal was recovered through a different procedure. In Morgan and Thi's work, the subband signals were twice oversampled, while in [35] the delayless structures were maximally decimated, with the optimal subband filters being related to the wideband system in a closed form. In [35], a special DFT analysis filterbank is used, where the polyphase components of the prototype filter represented fractional delays, so that there was no need for adaptive cross-filters and the unknown system could be modeled perfectly in a closed-loop scheme. This structure could be interpreted as a special case of the block adaptive filter, with a lower computational complexity than the conventional fullband LMS algorithm. In a later investigation, Huo *et al*. [36] exposed a weakness in Morgan's method that led to the production of spectral nulls in the passband of the implied synthesis filter. Two variations to the method, called DFT-2 Stacking and DFT-FIR Stacking, were proposed to mitigate this weakness. DFT-2 Stacking simply involves zero padding prior to the DFT and stacking. While in DFT-FIR stacking, the SAFs are processed through a polyphase-FFT synthesis filterbank. Extra computational complexity is required for the implementation using this method. Following this, Larson *et al*. [37] introduced a linear weight transform method. This method employs a linear matrix transformation of the subband filters, using both analysis and synthesis filters to recover the time domain adaptive filter. Another variation on Morgan's method employing the Hadamard transform to reconstruct the time domain adaptive filter was adopted by Hirayama *et al*. [38]. Although this structure has only been tested for the two-band case, the convergence performance is comparable to Morgan's structure [31] and the total number of subband taps is just half that of the latter scheme.

One side effect of the subband algorithms is the group delay associated with the analysis filterbank, which, accordingly, decreases the system's bounds of stability. Compensation methods have been proposed by DeBrunner *et al*. [39] to increase the bounds of stability by generating a set of new subband error signals to update the filter coefficients. The subband algorithm with delay compensation exhibited higher computational complexity compared with the conventional fullband LMS. In a separate study, Zhou and Qiu [40] have analyzed the subband/fullband weight transformation and the subband weight update process in the delayless structures. They investigated the adverse influences of the error path delay and introduced a closed-loop block update algorithm with error path delay compensation. Results for an acoustic echo cancellation application showed that this modified algorithm rapidly converges to small residual error with low computational complexity. A different technique was adopted by Sheikhzadeh *et al*. [41], where a weighted overlap-add (WOLA) synthesis instead of using direct IFFT or polyphase filterbanks to transform the SAFs back into the time-domain. Low-resource real-time implementations were targeted and as such did not involve long FFT or IFFT operations.

Recently, a partial updating strategy has been offered by Schüldt *et al*. [42], where the general idea is to only update the most misadjusted subband filters. In this way, the computational complexity of the delayless subband system can be reduced. Compared to a periodic

Table 3: A summary comparison of delayless subband adaptive filtering proposals

Source	Convergence rate	Computational Complexity	Comments
Morgan and Thi [31]	Faster	N/3	Spectrum mulling found
Boroujeny and Wang [33]	Moderate performance	2N/M	Delay decreased by 50% compared to fullband
Merched *et al.* [35]	Faster for colored input	N/3.7	No cross filters needed
Huo *et al.* [36]	Faster	>N/3	Uses very high-order analysis filters
Larson *et al*. [37]	Faster	>N/3	Not efficient for low number of subbands due to the use of RLS algorithm
Hirayama *et al.* [38]	Comparable to Morgan's	3N/2	High number of subbands not tested
DeBrunner *et al.* [39]	Faster	>N	Recommended for colored noise reduction
Zhou and Qiu [40]	Faster	Approximately N/2 in the best case	A potential increase in the computational complexity
Sheikhzadeh *et al*. [41]	Faster	>N/3	Suitable for low-order acoustic paths only
Schüldt *et al.* [42]	Slower	N/2	Residual noise performance is same as fullband

updating scheme, Schüldt *et al.*'s scheme showed a faster convergence speed in the acoustic echo cancellation situation. However, compared to fullband updating, the solution exhibits slightly slower convergence, while requiring about half of the computational complexity. Table 3 presents a comparison summary of different delayless structures.

CONCLUSIONS

In general, 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. Attempts to avoid cross filters have resulted in systems with even higher computational complexity. 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. Furthermore, it has been found that oversampled systems themselves color the subband signals, which results in under-modeling. As a result, increased bandwidth analysis filters have been proposed to solve this problem. Other methods of improving the performance of oversampled structures are based on linear and nonlinear optimization of analysis and synthesis filter banks. Delayless proposals have addressed the input-output delay while retaining convergence and complexity issues as advantages of subband decomposition. These systems are related in the way that they transform domain adaptive filtering. While reducing system delay, extra costs are introduced due to the utilization of FFT and IFFT in the transformation process. In the majority of subband schemes discussed in the literature, high order FIR filter banks are used as tools for signal decomposition and reconstruction. 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. Therefore, a low-cost alternative to existing classical FIR filter banks is still of interest. This should be accomplished with an acceptable processing delay. In addition, the improvements to the current subband adaptive filters may be further enhanced by a more elegant choice of their design and structure.

REFERENCES

1. Noor, A.O.A., 2012. Adaptive Noise Cancellation: Innovative Approaches. Lap Lambert, Germany. ISBN: 978-3-659-19193-0, pp: 25.
2. Johnson, J., E. Cornu, G. Choy and J. Wdowiak, 2004. Ultra Low-Power Sub- Band Acoustic Echo Cancellation for Wireless Headsets, In Proc. IEEE International Conference Acoustics, Speech and Signal Processing, Montreal, Quebec, Canada , 17-21 3: 57-60.
3. Haykin, S., 2002. Adaptive Filter Theory, 4th Edn., Prentice Hall, New Jersey.
4. Gilloir, A. and M. Vetterli, 1992. Adaptive Filtering in Subbands with Critical Sampling: Analysis, Experiments and Application to Acoustic Echo Cancellation, IEEE Transactions on Signal Processing, 40(8): 1862-1875.
5. Yoji Yamada, Hiroshi Ochi and Hitishi Kiya, 2004. A Subband Adaptive Filter Allowing Maximally Decimation, IEEE Journal on Selected Areas in Communications, 12(9): 1548-1552.
6. Usevitch, B.E. and M.T. Orchard, 1996. Adaptive Filtering Using Filter Banks, IEEE Transactionson Circuits and Systems II: Analog and Digital Signal Processing, 43(3): 255-265.
7. Petraglia, M.R., R.G. Alves and P.S.R. Diniz, 2000. New Structures for Adaptive Filtering in Subbands with Critical Sampling.IEEE Transactions on Signal Processing, 48(12): 3316-3323.
8. Sandeep, Pradhan S. and V.U. Reddy, 1999. A New Approach to Subband Adaptive Filtering, IEEE Transaction on Signal Processing, 47(3): 655-664.
9. Patrick A. Naylor, O¢guz Tanrıkulu and Anthony G. Constantinides, 1998. Subband Adaptive Filtering for Acoustic Echo Control Using Allpass Polyphase IIR Filterbanks, IEEE Transactions on Speech and Audio Processing, 6(2): 143-155.
10. Breining, C., P. Dreiscitel, E. Hansler, A. Mader, B. Nitsch, H. Puder, T. Schertler, G. Schmidt and J. Tilp, 1999. Acoustic echo control. An application of very-high-order adaptive filters, IEEE Signal Processing Magazine, 16: 42-69.
11. Hun Choiand, Hyeon-Deok Bae, 2007. Subband Affine Projection Algorithm for Acoustic Echo Cancellation System, EURASIP Journal on Advances in Signal Processing, doi: 10.1155/ 2007/75621.
12. Ozeki, K. and T. Umeda, 1984. An adaptive filtering algorithm using an orthogonal projection to an affine subspace and its properties, Transactions of the ICEIE,V.67-A, No. 2, pp: 126-132.

13. Mingsian R. Bai, Cheng-Ken Yang and Ker-Nan Hur, 2009. Design and Implementation of a Hybrid Sub-band Acoustic Echo Canceller (AEC). Elsevier Journal of Sound and Vibration, 321: 1069-1089. doi:10.1016/j.jsv.2008.09.053.
14. Kong A. Lee and Woon S. Gan, 2004. Improving the Convergence of the NLMS Algorithm Using Constrained Subband Updates, IEEE Signal Processing Letters, 11(9): 736-739.
15. Petraglia, M.R. and P. Batalheiro, 2008. Nonuniform Subband Adaptive Filtering With Critical Sampling, IEEE Transactions on Signal Processing, 56(2): 565-575.
16. Kim, S.G., C.D. Yoo and T.Q. Nguyen, 2008. Alias-Free Subband Adaptive Filtering With Critical Sampling, IEEE Transactions on Signal Processing, 56(5): 1894-1904.
17. Petraglia, M.R. and P.B. Batalheiro, 2004. Filter Bank Design for a Subband Adaptive Filtering Structure with Critical Sampling, IEEE Transactions on Circuits and Systems-I: Regular Papers, 51(6): 1194-1202.
18. Mohammad Shams Esfand Abadi, 2009. Proportionate normalized subband adaptive filter algorithms for sparse system identification, Elsevier Signal Processing, 89: 1467-1474. doi:10.1016/j.sigpro.2008.12.025.
19. Donald L. Duttweiler, 2000. Proportionate Normalized Adaptation in Echo Cancellers, IEEE Transactions on Speech and Audio Processing, 8(5): 508-518.
20. Mehran Nekuii and Mojtaba Atarodi, 2004. A fast Converging Algorithms for Network Echo Cancellation, IEEE Signal Processing Letters, 11(4): 427-430.
21. Andy W.H. Khong, Patrick A. Naylor and Jacob Benesty, 2007. A Low Delay and Fast Converging Improved Proportionate Algorithm for Sparse System Identifications, EURASIP Journal on Audio, Speech and Music Processing, Volume 2007,Article ID 84376, 8 pages. doi:10.1155/2007/84376.
22. Shuichi Ohno and Hideaki Sakai, Convergence behavior of the LMS algorithm in subband adaptive filtering, Elsevier Signal Processing, 81: 1053-1059. doi:10.1016/S0165-1684(00)00263-2.
23. Akansu, A.N. and Mark J.T. Smith, 1995. Subband And Wavelet Transforms Chapter12, Kluwer Academic Publishers Group NJ.
24. DeLeo´N P. and D.M. Etter, 1995. Experimental results with increased bandwidth analysis filters in oversampled, subband acoustic echo cancellers, IEEE Signal Processing Letters, 2(1): 1-3.
25. Harteneck, M., J.M. Pàez-Borrallo and R.W. Stewart, 1998. An Oversampled Subband Adaptive Filter Without Cross Adaptive Filters, Elsevier Signal Processing, 64(1): 93-101. doi:10.1016/S0165-1684(97)00179-5.
26. Sridharan, M.K., 1998. Subband adaptive Filtering: Oversampling approach, Elsevier Signal Processing, 71: 101-104. doi:10.1016/S0165-1684(98)00173-X.
27. Harteneck, M., S. Weiss and R.W. Stewart, 1999. Design of Near Perfect Reconstruction Oversampled Filter Banks for Subband Adaptive Filters, IEEE Transactions on Circuits and Systems-II: Analog and Digital Signal Processing, 46(8): 1081-1085.
28. Chin, W.H. and B. Farhang-Boroujeny, 2001. Subband Adaptive Filtering With Real- Valued Subband Signals for Acoustic Echo Cancellation, IEE Proceedings. Image Signal Processing, 148(4): 283-288.
29. Petraglia, M.R. and P.R.V. Piber, 2003. Filter Bank Design for Oversampled subband Adaptive Filtering Structures, Electronics Letters, pp: 39.
30. Cedric Yiu, K.F., Nedelko Grbic, Sven Nordholm and K.L. Teo, 2006. A hybrid Method for the Design of Oversampled Uniform DFT filter bank, Elsevier Signal Processing 86: 1355-1364. doi:10.1016/j.sigpro.2005.02.023.
31. Morgann, D.R. and J.C. Thi, 1995. A Delayless Subband Adaptive Filter Architecture, IEEE Transactions on Signal Processing, 43(8): 1819-1830.
32. Shynk, J.J., 1992. Frequency Domain and Multirate Adaptive Filtering, IEEE Signal Processing Magazine, 9: 14-37.
33. Farhang-Boroujeny B. and Zhongjun Wang, 1997. Adaptive filtering in subbands: Design issues and experimental results for acoustic echo cancellation, Elsevier Signal Processing, 61(3): 213-223.
34. Vaidyanathan, P.P. and T.Q. Nguyen, 1987. Eigenfilters: A New Approach to Least-Squares FIR Filter Design and Applications Including Nyquist Filters, IEEE Transactions on Circuits and Systems, 34(1): 11-23.
35. Merched, R., P.S.R. Diniz and Mariane R. Petraglia, 1999. A New Delayless Subband Adaptive Filter Structure, IEEE Transactions on Signal Processing, 47(6): 1580-1591.
36. Huo, J., S. Nordholm and Z. Zang, 2001. New weight transform schemes for delayless subband adaptive filtering, Proc. of IEEE Global Telecom Conf., pp: 197-201.

37. Larson, L., J. Mark De Haan and I. Claesson, 2002. A new subband weight transform for delayless subband adaptive filtering structures, Proc. of IEEE DSP Workshop, pp: 201-206.
38. Hirayama, N., H. Sakai and S. Miyagi, 1999. Delayless subband adaptive filtering using the Hadamard transform, IEEE Transactions on Signal Processing, 47: 1731-1734.
39. Victor DeBrunner, Linda S. DeBrunner and Longji Wang, 2004. Sub-Band Adaptive Filtering With Delay Compensation for Active Noise Control, IEEE Transactions on Signal Processing, 52(10): 2932-2937.
40. Yin Zhou and Xiaojun Qiu, 2007. An Error Path Delay Compensated Delayless Subband Adaptive Filter Architecture, Elsevier Signal Processing, 87(11): 2640-2648.
41. Hamid Sheikhzadeh, Robert L. Brennan, Zamir Khan and Kevin R.L. Whyte, 2005. Low Resources Delayless Subband Adaptive Filtering Using Weighted overlap add, In Proceedings of the 13th European Signal Processing Conference (EUSIPCO 2005). September 4-8.
42. Christian Schüldt, Fredric Lindstrom and Ingvar Claesson, 2008. A Low- Complexity Delayless Selective Subband Adaptive Filtering Algorithm, IEEE Transactions on Signal Processing, 56(12): 5840-5850.
43. Noor, A.O.A., S.A. Samad and A. Hussain, 2010. Improved Adaptive Noise Cancellation using Allpass IIR Filter Banks. Transactions of Hong Kong Institution of Engineers, HKIE, 17(3): 45-51.
44. Noor, A.O.A., S.A. Samad and A. Hussain, 2011. Adaptive Filtering using Subband Processing: Application to Background noise Cancellation. In "Adaptive Filtering" I-Tech: Vienna, Austria, 2011; pp: 109-134.