Sub-band Implementation of Adaptive Nonlinear Filter for Adaptive Nonlinear Echo Cancellation

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Abstract—**The adaptive Volterra filter has been successfully applied in nonlinear acoustic echo cancellation (AEC) systems and nonlinear line echo cancellation systems, but its applications are limited by its required computational complexity and slow convergence rate, especially for systems with long memory length. In this paper, we first apply a more general nonlinear filter, the function expansion nonlinear filter, in the acoustic echo cancellation ─ the Volterra filter can be regarded as special case of the function expansion nonlinear filter. Then by leveraging to a multi-channel configuration of the function expansion nonlinear filter and the sampling theory for nonlinear systems, we extend linear sub-band delay-less adaptive filter techniques to develop an efficient sub-band implementation of the adaptive function expansion nonlinear filter. The developed sub-band configuration of the adaptive nonlinear filter can greatly improve the convergence rate and reduce the computational complexity of nonlinear echo cancellers, which is shown by analyses and simulations.**

Index Terms—**Adaptive nonlinear filter, Adaptive Echo Cancellation, Sub-band implementation.**

I. Introduction

Acoustic echoes, arising from the acoustic coupling between the receive- and transmit-paths of a telecommunication terminal, could greatly affect the quality of voice communication in wireless communication systems, VoIP services, hands-free telephone systems, etc. Acoustic echo cancellation (AEC) is an effective technique to suppress the echo effect and improve the communication system performance. The configuration of an AEC system is shown in Figure 1. Most AEC techniques do not consider the nonlinear distortion caused by amplifiers, loudspeakers, and nonlinear effects in the vibration of the enclosure. However, recently, many researchers have found that the AEC system performance could be greatly improved by considering the nonlinearities existing in the system.

Based on "Efficient Adaptive Nonlinear Echo Cancellation, Using Sub-Band Implementation of the Adaptive Volterra Filter", by D. Zhou, et al., which appeared in the Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2006, Toulouse, France, May 2006. © 2006 IEEE.

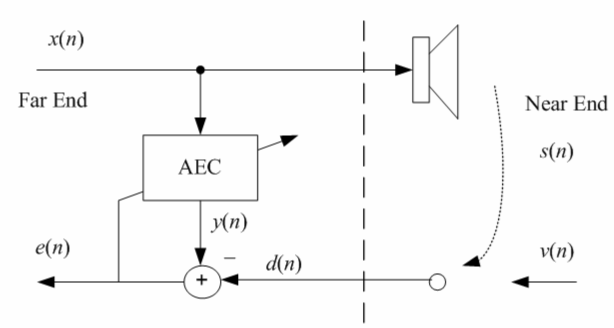

Figure 1. Configuration of acoustic echo cancellation

Consequently, nonlinear acoustic echo cancellation (AEC) techniques, e.g. the algorithms in [1]-[3], have been developed. The nonlinear distortion has also been studied in the line echo cancellation configuration [4].

The adaptive Volterra filter has been applied in nonlinear acoustic echo cancellation (AEC) and nonlinear line echo cancellation systems to identify and track the time-varying nonlinear impulse response (NIR) from the far-end signal to the echo signal, which usually includes the A/D converter, nonlinear loudspeaker, room transfer function and other components [4]. Besides the Volterra filter, many other adaptive nonlinear filters have been applied to efficiently solve the adaptive nonlinear echo cancellation, e.g. the adaptive orthogonalized power filters [13] and the raised-cosine function based filter [14]. In our research, we find that most of these nonlinear filters can be included in a function expansion nonlinear filter structure. Consequently, in this work, we first apply the function expansion nonlinear filter in the acoustic echo cancellation ─ the Volterra filter can be regarded as special case of the function expansion nonlinear filter.

Most adaptive nonlinear filters, including the Volterra filter, suffer from a large computational complexity and are slow to converge. These problems are even more significant in nonlinear AEC systems due to the long memory length of the NIR and the wide speech spectral dynamics [5]. Many researchers working in this area have proposed different methods and simplified structures to speed convergence and reduce the computational burden of adaptive nonlinear filter, e.g. the affine projection based adaptive Volterra filter [1], cascaded structures implementation [2], nonlinear orthogonalized power filter

[14], and the MMD (multi-memory decomposition) structure [3].

In this paper, we successfully solve the convergence rate and heavy computational cost by using sub-band implementation of the function expansion nonlinear filter. The delay-less sub-band implementations of adaptive linear filters are proposed in [7], [8]. Without introducing the signal path delay, the proposed methods can greatly increase the convergence speed and reduce the computational complexity of large-order linear AEC systems and active noise control (ANC) systems. However, due to the complexity and spectral outgrowth caused by the nonlinearities, no sub-band version of the adaptive nonlinear filters was typically available before the introduction of the sub-band implementation of adaptive Votlerra filter in our previous work [15]. This paper is a expanded and enhanced version of our previous work − we extend our previously developed subband implementation of adaptive Volterra filter technique to a more general nonlinear filter, the function expansion nonlinear filter, and add more detailed discussion.

In summary, we use the recently developed sampling theory of nonlinear systems and the multi-channel structure of the function expansion nonlinear filter to propose an efficient delayless sub-band adaptive nonlinear filter. Our new sub-band configuration is based on a combination of Morgan's configuration [7] and DeBrunner's configuration [8], which is suitable for adaptive nonlinear filter implementation. Like its linear counterparts, our proposed sub-band implementation of the adaptive nonlinear filter demonstrates fast convergence and computational efficiency for a large-order system, which has proved to be especially useful in nonlinear AEC systems when the NIR has a large memory and speech is the main reference signal.

The paper is arranged as follows. We first present some preliminary backgrounds including the function expansion nonlinear filter and its multi-channel representation as well as the sampling theory of nonlinear system in Section II. Based on these preliminary backgrounds, in Section III we derive an efficient sub-band implementation of the adaptive nonlinear filter and apply the developed adaptive nonlinear filter to solve the AEC problem. Detailed computational cost is given in Section IV. Simulations are provided in Section V followed by conclusions in Section VI.

II. PRELIMINARY BACKGROUND

In nonlinear echo cancellation, the nonlinear system can be modeled and approximated by the truncated Volterra series model [1]-[4], [9], or other nonlinear model [13], [14]. In this work, we use a more general nonlinear system model, i.e., the function expansion nonlinear filter, to model the relationship between the echo signal $y(n)$ and the far-end signal

$x(n)$ $$y(n) = \sum_{q=1}^{Q} w_q(n)\phi_q[\overline{x}(n)] \quad (1)$$

where $\overline{x}(n)$ represents the input sequence [i.e., $x(n)$, $x(n-1)$, $\cdots$, $x(n-N)$], $w_q(n)$ is the qth coefficient at time n, Q is the total number of terms, and $\phi_q[\overline{x}(n)]$ belongs to a set of linearly independent functions of $\overline{x}(n)$, which generates nonlinear states. This general function expansion nonlinear filter is well-known to researchers working in the area of nonlinear signal processing. The functional expansion provides a nonlinear filter that is a subset of the FLANN model [16]. Furthermore, a linear filter is a special case of this function expansion nonlinear filter. Also, this functional expansion is the truncated Volterra filter of [2] when

$$\phi_q[\overline{x}(n)] = x(n-n_{q,1})x(n-n_{q,2})\cdots x(n-n_{q,P_q}) . \quad (2)$$

Here $n_{q,1}$, $n_{q,2}, \cdots$ n_{q,P_q} are arbitrary integers representing delay. The maximum delay determines the memory size, and P_q represents the order of the nonlinearity.

Consequently, we can develop the multi-channel implementation of this nonlinear filter as the multi-channel structure of the Volterra filter (referred to as the diagonal representation in [17]). For C channels, we group the nonlinear states $\phi_q[\overline{x}(n)]$ in (1) into several groups $\mathbf{x}_1(n)$, $\mathbf{x}_2(n)$, $\cdots$, $\mathbf{x}_C(n)$, with

$$\mathbf{x}_c(n) = \left[\phi_{q_{c,0}}[\overline{x}(n)], \quad \phi_{q_{c,1}}[\overline{x}(n)], \quad \ldots, \quad \phi_{q_{c,N_c}}[\overline{x}(n)] \right]^T \quad (3)$$

where $1 \le c \le C$, and $q_{c,0}$, $q_{c,1}$, …, q_{c,N_c} are integers, such that the elements within each group have a time-delayed relationship, e.g., $\phi_{q_{c,1}}[\overline{x}(n)]$ is obtained by delaying $\phi_{q_{c,0}}[\overline{x}(n)]$ by one sample, …, and $\phi_{q_{c,N_c}}[\overline{x}(n)]$ is obtained by delaying $\phi_{q_{c,0}}[\overline{x}(n)]$ by N_c samples. So, we can define the state vector as:

$$\mathbf{x}(n) = \left[\mathbf{x}_1^T(n) \quad \mathbf{x}_2^T(n) \quad \ldots \quad \mathbf{x}_C^T(n) \right]^T . \quad (4)$$

Correspondingly, we can group the coefficients of the nonlinear filter in (1) as

$$\mathbf{h}(n) = \left[\mathbf{h}_1^T(n) \quad \mathbf{h}_2^T(n) \quad \ldots \quad \mathbf{h}_C^T(n) \right]^T \quad (5)$$

with

$$\mathbf{h}_c(n) = \left[w_{q_{c,0}}(n) \quad w_{q_{c,1}}(n) \quad \ldots, \quad w_{q_{c,N_c}}(n) \right]^T \quad (6)$$

corresponding to the state groups in (3). As a result, we can write the nonlinear filter in (1) as

$$y(n) = \mathbf{h}^T(n)\mathbf{x}(n) \quad (7)$$

and in the multi-channel form as

$$y(n) = \sum_{c=1}^{C} \mathbf{h}_c^T \mathbf{x}_c(n) = \sum_{c=1}^{C} y_c(n) . \quad (8)$$

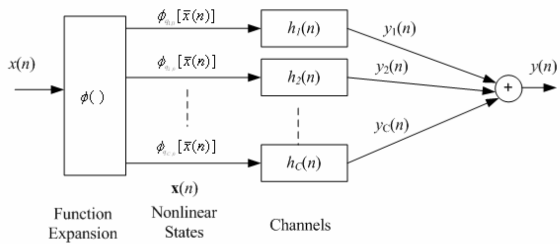

Figure 2. Multi-channel implementation of the function expansion nonlinear filter.

By this arrangement, we only need to calculate the first nonlinear state of each group in (3) and then the remaining terms are obtained by delay. The structure of the multi-channel implementation of this nonlinear filter is shown in Fig. 2, where $h_1(n)$, $h_2(n)$, …, $h_C(n)$ are filters with corresponding coefficient vectors defined in (6). The function expansion box in Fig. 2 generates the nonlinear states required for each channel. The output of the nonlinear filter can be regarded as the sum of the outputs of several linear filters (or channels). Here, C is the maximum number of channels: for a memory length of N and pth-order truncated Volterra series, C = $(N+P)!(N!P!)^{-1}-1$ [18]. As a result, the number of channels increases as the order and/or the memory size increase. Filter $h_1(n)$ represents the linear component of the nonlinear filter and the higher-order channels $h_i(n)$ ($i>1$) represent the nonlinear components.

The nonlinear echo cancellation problems can be regarded as an adaptive nonlinear system identification problem, i.e. the adaptive identification of the NIR. Using the multi-channel implementation of the function expansion nonlinear filter, we see that to identify a nonlinear system is to identify each channel's coefficients, the $H_i(n)$ ($i=1,\ldots,C$) in Fig. 2.

It is well known that to identify a linear system we should sample the input signal at its Nyquist frequency or higher. The input to the high order channels have a frequency much higher than the input $x(n)$. So it seems we need to sample the input $x(n)$ at a much higher frequency than its Nyquist frequency or we need to up-sample the nonlinear states of the higher order channels. However, a recent research result in [11] proves that, to identify the nonlinear system, we only need to sample the input signal $x(n)$ at its Nyquist frequency – exactly at twice the maximum frequency found in the input signal $x(n)$. Based on this theory, it is not necessary to up-sample the nonlinear states in $X_i(n)$ ($i>1$). This means we don't need to consider the nonlinear spectral outgrowth to identify the high-order channels, i.e. we can treat each channel in Fig. 2 just like we would a linear filter.

III. SUB-BAND IMPLEMENTATION OF ADAPTIVE NONLINEAR FILTER

From the above analysis, in the multi-channel implementation of the nonlinear filter we can regard each channel in Fig. 2 as a linear filter without extra consideration concerning the spectral outgrowth. As a result, we can extend the linear sub-band adaptive filter techniques to develop an adaptive sub-band nonlinear filter based on the multi-channel structure. The configuration of the developed sub-band adaptive nonlinear filter is shown in Fig. 3. If one interprets this figure as a nonlinear AEC configuration, $x(n)$ represents the far-end signal and so is the reference signal provided to the adaptive nonlinear filter, which in this case would usually be speech. $P(n)$ is the NIR; $s(n)$ represents the acoustic echo [1].

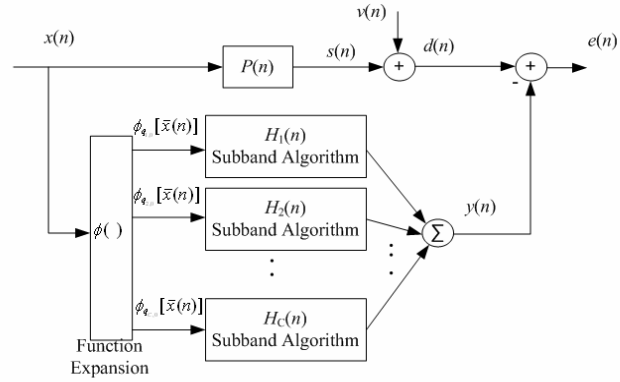

Figure 3. Sub-band adaptive function expansion nonlinear filter based on multi-channel configuration

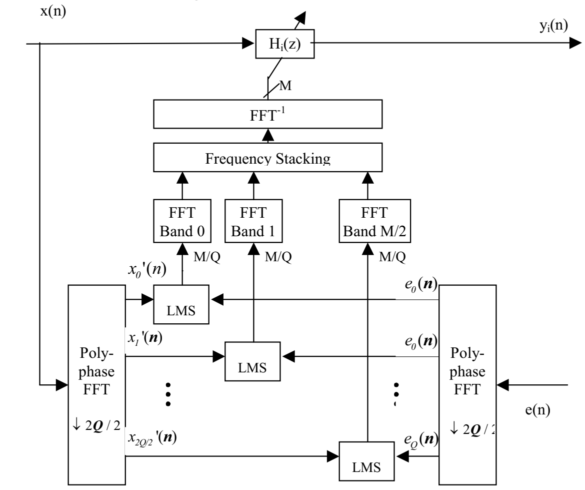

Figure 4. Delayless sub-band adaptive linear filter based on the Morgan configuration

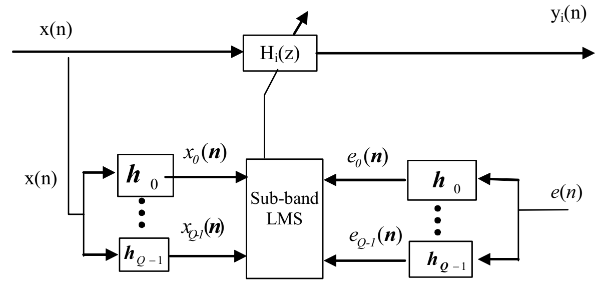

Figure 5. Delayless sub-band adaptive linear filter based on the DeBrunner configuration

The conventional linear sub-band adaptive filters induced delay in the signal path through the introduction of the sub-band filters into that path. This delay limits the application of AEC [7]. Morgan *et al* [7] proposed the delayless sub-band adaptive linear filter as shown in Figure 4. In that configuration, the coefficients for each sub-band are updated independently and then combined through an FFT to yield the broadband coefficients. The Morgan configuration can greatly reduce the computational complexity when the linear system has a large order. However, in order to have a good approximation for each sub-band frequency response, each sub-band needs to have at least 4 coefficients. Also, to increase the convergence speed, at least 4 sub-bands are required. These limit the application of the Morgan sub-band configuration to applications with large-order channels. DeBrunner et. al. [8] introduced another configuration for the sub-band adaptive linear filter as shown in Figure 5 that directly updates the broadband coefficients based on all sub-band signals. Without up-sampling and down-sampling, the DeBrunner configuration has no limitations on the adaptive filter order; however, the computational complexity will increase as the number of channels increases. In the multi-channel implementation of the nonlinear filter, different channels usually have different lengths for fixed memory nonlinear models. Take the Volterra filter for example, the linear terms of $x(n)$ have a length N+1, but the channel with state $x(n)x(n-N)\ldots x(n-N)$ only has length one. As a result, neither the Morgan nor the DeBrunner configuration is suitable for our sub-band adaptive nonlinear filter.

Here, we proposed a new sub-band adaptive nonlinear filter by combining the two delayless sub-band configurations. This means that when the order of the channel is less than 64, we can implement the DeBrunner configuration; otherwise, we implement the Morgan configuration. As a result, we combine Figs. 3, 4, and 5, to yield our proposed sub-band adaptive nonlinear filter. By sub-band decomposition, we can decrease the eigenvalue spread in each sub-band, and each sub-band can be updated using different step sizes. As a result, the convergence speed is greatly improved, and especially for colored inputs such as speech.

IV. SUB-BAND IMPLEMENTATION COST

To demonstrate the computational advantage of our proposed sub-band adaptive nonlinear filter, the computational complexities of full-band and sub-band implementation of adaptive Volterra filter are calculated. We calculate the number of real multiplications per iteration for updating one channel of the adaptive Volterra filter with a total of M coefficients. We assume that each channel is updated by the simple least mean square (LMS) method in both the full-band and sub-band configurations. Note, however, that other updating methods can also be applied in our algorithm, such as the RLS and affine projection algorithms to further increase the convergence rate. For the full-band LMS based adaptive Volterra filter, we find that the LMS algorithm requires

$$R_F = 2M + 1 \tag{9}$$

real multiplications – one M for filtering and another M is required to calculate the instantaneous gradient, and one more multiplication is required for applying the step size. The number of real multiplications for one channel of length N in Fig. 3 based on Morgan's configuration can be obtained from [7]:

$$R_M = N + \frac{4(P+2N)}{Q} + \frac{16N}{Q^2} + 2\log_2(Q) + 3\log_2(N) \tag{10}$$

where Q is the number of sub-bands and P is the length of the prototype filter. The number of multiplications for one channel based on DeBrunner's configuration can be obtained from [8]:

$$R_D = Q(2L+N) + N + 1 \tag{11}$$

where L is the length of the sub-band filter. Thus, the total number of multiplications required for the sub-band adaptive Volterra filter is a combination of R_M and R_D. This computational complexity can be further reduced by using the recently developed multiple input multipliers [12] and sharing the sub-band error signals for different channels. From these calculations, we find that if most channels in the Volterra filter have large order, our configuration can greatly reduce the computational cost. For a low-order nonlinear system, the sub-band implementation will somewhat increase the computational complexity. However, this cost is offset by the fast convergence rate as shown in our next section. The recently introduced affine projection adaptive Volterra filter can greatly increase the convergence speed of the echo canceller. However, when compared to the full-band normalized LMS algorithm, the computational complexity increase is proportional to the order of the affine projection algorithm.

V. SIMULATIONS OF THE NEW ECHO CANCELLATION

We simulate the nonlinear AEC using the three approaches: 1) our proposed sub-band adaptive nonlinear filter as shown in Fig. 3, 2) the full-band adaptive nonlinear filter of [3], and 3) the affine projection adaptive nonlinear algorithm with order 3 in [1]. To facilitate our simulation, the NIR is modeled as a Volterra filter with three channels: the first channel is a linear channel with length 128, while the second and third channels are nonlinear channels of length 128 and inputs $x(n)x(n-1)$ and $x(n)x(n-3)$, respectively. These are typical lengths of the impulse response for the hardest receivers. The nonlinear channels' coefficients are shown in Fig. 6.

The speech signal $x(n)$ is a speech signal measured in our laboratory with sampling frequency of 20k Hz. The full-band adaptive nonlinear filter and our proposed sub-band adaptive nonlinear filter are updated using the normalized LMS algorithm. The step sizes of the adaptive nonlinear filters for the different channels and the different sub-bands are tuned to ensure that the adaptive filters converge at their fastest convergence rate. The performance of the nonlinear AEC is measured by the echo return loss enhancement (ERLE):

$$ERLE = 10\log_{10}\frac{E(d^2(n))}{E(e^2(n))} \tag{12}$$

The ERLE versus time for the nonlinear AEC using the full-band NLMS, proposed sub-band NLMS and the affine projection Volterra filters are shown in Fig. 7. Here, we find that the nonlinear AEC based on our proposed sub-band adaptive Volterra filter has a much faster convergence rate when compared to the one using the full-band adaptive Volterra filter. Our proposed algorithm does, however, converge slightly more slowly than the affine projection algorithm. Note, however, that the affine projection algorithm requires far more computational complexity than our proposed subband algorithm.

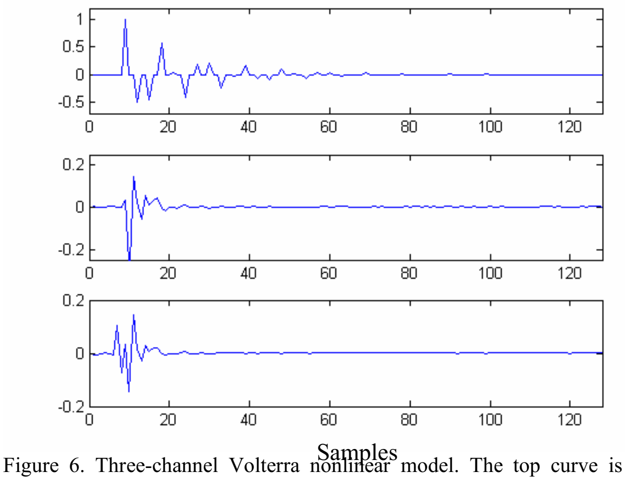

Figure 6. Three-channel Volterra nonlinear model. The top curve is linear channel coefficients; the middle and bottom curves are nonlinear channels.

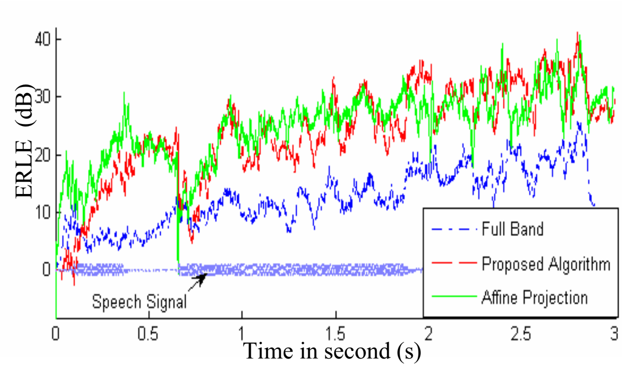

Figure 7. ERLE for different AEC algorithms

VI. Conclusions

In this paper, based on the sampling theory for nonlinear system and multi-channel implementation of the general function expansion nonlinear filter, an efficient delayless sub-band adaptive nonlinear filter algorithm was proposed for the first time, and was applied to cancel nonlinear echoes in wireless communication systems, VoIP services, hands-free telephone systems, etc.. The developed delayless sub-band implementation combines the advantages of both Morgan's and DeBrunner's delayless sub-band configuration, which is more suitable for adaptive nonlinear filter implementation. The function expansion nonlinear filter includes, but is not limited to, the Volterra filter. As a result, our proposed techniques have very broad applications. Simulations and analyses show that our method can increase the convergence rate of an adaptive nonlinear filter and reduce the computational complexity for large order systems, which in turn improves the performance of the nonlinear echo cancellation systems. Other direct applications of our proposed sub-band adaptive nonlinear filter algorithm will be in nonlinear system identification and adaptive nonlinear interference cancellation.

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