Echo Cancellation by Adaptive Combination of Nsafs Adaptedbystocastic Gradient Method

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Abstract

In acoustic echo cancellation the highly correlated speech input signal and very large impulse response path of echo signal will slow down the convergence rate of adaptive filters if fullband adaptive filter is used. To solve these problems subband adaptive filters are used. Adaptive combination methods provide an interesting way to improve adaptive filter's performance. A tradeoff between fast convergence rate and small steady state mean square error (MSE) in adaptive combination is achieved by stochastic gradient algorithm. The individual each filter is independently adapted by it's own error signal while combination is adapted by sum of squared subband errors as the cost function. Adaptive combination of normalized sub band adaptive filters is used. In our proposed method, adaptive combination of sub band signals before going to the adaptive filters. Experimental results show that the combination method can obtain both fast convergence rate and small steady state MSE by using less number of adaptive filters.

General Terms: Acoustic Echo Cancellation, subband adaptive filters, echo return loss enhancement.

Keywords: Round Trip Delay (RTD), Acoustic Echo Cancellation (AEC), Normalized Least Mean Square Algorithm (NLMS), Mean Square Error (MSE), Subband Adaptive Filters (SAF), Adaptive Combination Normalized Subband Adaptive Filters (NSAF) ,signal to noise ratio (SNR).

1. Introduction

The history of echo cancellation begins on 10th July 1962.In telephones and teleconferencing; a reflection can occur where there is an impedance mismatch. If the reflected signal reaches the far end subscriber with a RTD of a few milliseconds then it is perceived as reverberator. If RTD exceeds a few tens of milliseconds the reflection is known as distinct echo [1].

Echo suppressor was used to remove echo which introduces a very large transmission loss in return path. A new technique that did not interrupt the echo return path called echo cancellation. The AEC estimates the characteristics of the echo path and generates a replica of the echo. The echo is then subtracted from the received signal. Adaptive filters are used as echo canceller. The normalized least-mean-square (NLMS) algorithm is one of the most popular adaptive filters. Speech input signal of the adaptive filter is highly correlated and the impulse response of the acoustic echo path is very long.These two characteristics will slow down the convergence rate of the acoustic echo canceller. So sub band adaptive filtering is used to solve these problems. In SAFs, each sub band uses an individual adaptive sub filters. Recently, an adaptive combination of fullband adaptive filters has been proposed in [8], and its mean-square performance has been analyzed in [9]. More recently, a combination of SAFs for AEC has been proposed [10], which is based on a conventional sub band structure. In this paper we propose a new scheme for adaptive combination of subband adaptive filters deal with the tradeoff problem encountered in AEC which are implemented by NSAFs. The NSAF can be viewed as a subband generalization of the NLMS based adaptive filter. In the proposed combination, mixing parameter that controls the combination is adapted by means of a stochastic gradient algorithm which employs the sum of squared subband errors as the cost function.

Section II represents the Simulink model for fullband adaptive filter acts as acoustic echo cancellation [2].Section III represents sub band adaptive filter and adaptive combination of normalized sub band adaptive filters. Section IV improved adaptive combination of normalized subband adaptive filters. Section v represents Experiment results.

Notation: Symbols in uppercase letters are used for matrices and in lower cases are used for vectors. Other notations are as follows: (.) T represents transpose,E(.) is expectation, $\|\cdot\|$ represents the Euclidean vector, and *diag*(□) stands for a diagonal matrix.

2. Simulink Model Of Fullband Adaptive Filter Acts As Acoustic Echo Cancellation

A block diagram of AEC is shown in Fig.1 [2].

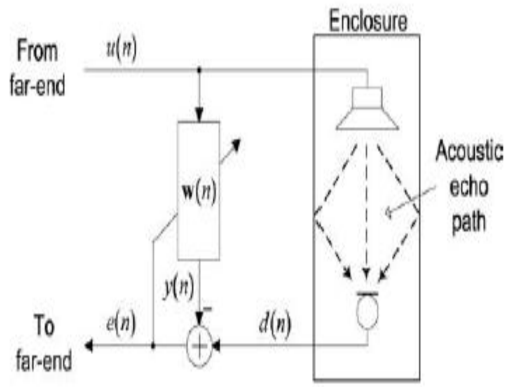

Fig. 1: Block diagram of fullband adaptive filter acts as AEC

Speech signal originating from loudspeaker is received by microphone passing through acoustic echo path. The acoustic echo is removed by adaptive filters. The d (n) signal contains the speech signal and noise signal. The goal of the adaptive filter **w** (n) is to produce a replica of the echo signal *y* (*n*). *y*(*n*) can be used to cancel the echo by subtracting it from the microphone signal *d*(*n*) resulting in error free signal e(n)[3].Algorithm for AEC is as follows [2]:

Adjustable tap weights can be expressed as:

$w(n) = [w_0\ (n), w_1\ (n), \ldots . w_{M-1}\ (n)]^T = w^T\ (n)u(n)$..(1)

Input signal can be expressed as

U (n) = $[u(n), u(n-1), \ldots u(n-M+1)]^T$ …. (2)

The output signal y(n) of adaptive filter is the multiplication of w(n) and u(n).

Y (n) = $\sum_{m=0}^{M-1} w_m\ (n)u(n-m)$= $w^T\ (n)u(n)$…. (3)

The error signals difference between the desired response d (n) and filter response y (n) is expressed as:

e (n)=d(n)- $w^T\ (n)$u(n)……..(4)

3. Simulink Model of Nsaf and Its Adaptive Combination

3.1 Simulink Model of NSAF

The block diagram of normalized subband adaptive filter is shown in fig. 2[5,6].

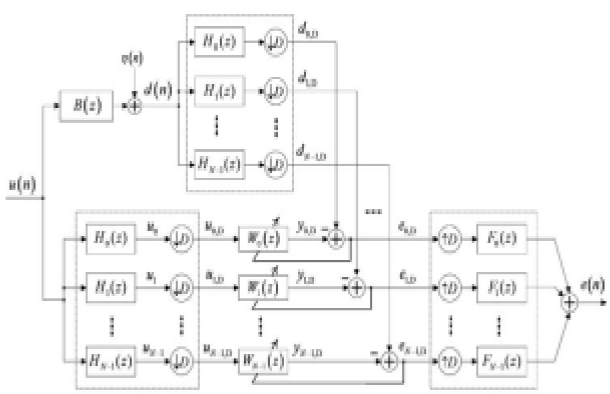

Fig. 2: Block diagram of NSAF

The input speech signal u (n) and desired output d(n) are decomposed into N spectral bands using analysis filters. Analysis filtering is then performed in these sub-bands by a set of independent filters (h0 (n), h1 (n),…, hM-1(n))[2].The sub band signals are further processed by individual adaptive sub filters Wi(z).Each sub band is computing error signal e(n). By updating the tap weights, minimizes the sub band error signal. The full band error signal *e(n)* is finally obtained by interpolating and recombining all the subband error signals using a synthesis filter bank. The updating equation of NSAFs is written as follows [3]:

$w_i(n+1) = w_i(n) + \mu_i \sum_{i=0}^{N-1} \frac{u_{i(n)}}{\delta + \|u_{i(k)}\|^2} e_i(n)$…..(5)

Where i=1,2,…N-1. Where $u_i(k) = [u_i(kN), u_i(kN-1) \ldots, u_i(kN-M+1)]^T$,M is the length of the adaptive filter **w**ˆ (*k*) ,μ is the step-size, and δ is the regularization parameter[3].

3.2 Simulink Model of Adaptive Combination of NSAFs

The block diagram of adaptive combination of normalized subband adaptive filters is shown in fig.3[9].

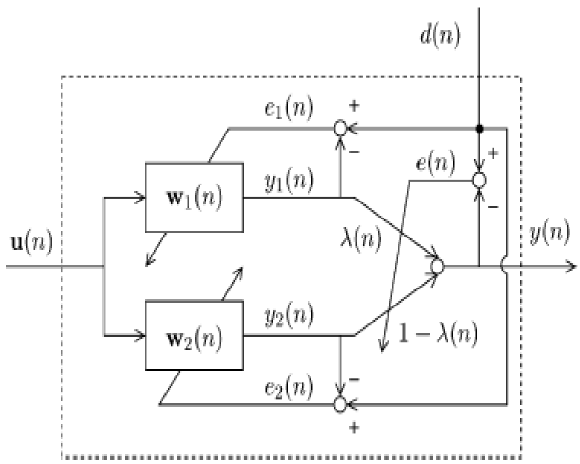

Fig. 3: Adaptive combination of NSAFs

A large step size yields a fast convergence rate but also a large steady state MSE [7].To achieve fast convergence rate and small steady state MSE, adaptive combination of subband adaptive filters is done .So that large step sizes adaptive filters give fast convergence rate and small step sizes adaptive filters give small steady state MSE.So idea becomes to adapt different step sizes filters independently and combination is carried out by using a mixing parameter lambda.

The input signal is U (n)=$[u(n), u(n-1), \ldots u(n-M+1)]^T$, weight vectors are $w(n) = [w_0(n), w_1(n), \ldots . w_{M-1}(n)]^T = w^T(n)u(n)$. So output becomes y(n)=$w^T(n)u(n)$. The update eq. of sub band adaptive filter is given in eq. 5.

$w_i(n+1) = w_i(n) + \mu_i \sum_{i=0}^{N-1} \frac{u_{i(n)}}{\delta + \|u_{i(k)}\|^2} e_i(n)$ Where

$e_1(n)$= d(n)-y_1(n) and $e_2(n)$= d(n)-y_2(n) and

$y_1(n) = w_1^T(n)u_n$, $y_2(n) = w_2^T(n)u_n$. Consider $\mu_1 > \mu_2$, then $w_1(n)$ adaptive filter has faster convergence rate and large steady state MSE whereas $w_2(n)$ has slower faster convergence rate but small steady state MSE.So our purpose is to get large convergence rate and small steady state MSE ,So combine both adaptive filters. The output of overall filter is: Y(n)=$\lambda(\boldsymbol{n})$ y_1(n)+[1- $\lambda(\boldsymbol{n})$] y_2(n)………(6) where **λ** is mixing parameter. The overall filter with tap weight factor of the form is: w(n)=$\lambda(\boldsymbol{n})w_1$(n)+ [1- $\lambda(\boldsymbol{n})$] w_2(n).For adaptation of mixing parameter $\lambda(\boldsymbol{n})$,use stocastic gradient method to minimize error of overall filter $e^2(n) = [d(n) - y(n)]^2$.

However instead of directly adjusting (n), we will adapt a variable $\alpha(n)$ that defines $\boldsymbol{\lambda}$(n) as a sigmoidal function. (n)=sgm [α(n)]=$\frac{1}{1+e^{-\alpha(n)}}$.......(7)

The update eq. for α(n) is given as:

α(n+1)=α(n)+μ e(n) [y_1(n)- y_2(n)]$\boldsymbol{\lambda}$(n)[1-$\boldsymbol{\lambda}$(n)]...........(8)

where μ is the step size for adapting α(n).since the mixing parameter is defined by the sigmoidal function[15],which insists the mixing parameter to lie exactly inside the interval (0,1), this combination is convex combination.[14][3].

4. Improved Adaptive Combination Of Normalized Subband Adaptive Filters

In improved adaptive combination of normalized subband adaptive filters,we take the following assumption.

1) d(n) and u(n) are related by a linear regression model d(n)= w_o^T (n)u(n)+ $\eta(n)$

for some unknown weight vector w_0 of length M and where $\eta(n)$ is an independent distributed noise.

2) The initial condition w_1 (0), w_2(0) and a(0) are independent of u(n),d(n) or all n.

3) $E\{\mathbf{u}(n)\} = \mathbf{0}, E\{\mathbf{u}(n)\mathbf{u}^T(n)\} = \mathbf{R}, E\{d(n)\} = 0$, and $E\{e_0(n)\} = 0$.[1]

A large convergence rate and small steady state MSE can be greatly achieved by using less amount of adaptive filters as comparison to the previous adaptive combination method. This can be achieved by using the idea of adaptive combination of speech input signal before going to the NSAF.

5. Experimental Results

The full-band and sub-band systems, adaptive combination of subband adaptive filters and its improvement were modeled in Matlab Simulink and many simulations for different inputs and number of sub-bands were performed. For the adaptive algorithm several different algorithms can be used, but the most common one is the normalized least mean squares (NLMS). The order of the NLMS filters was chosen from N=64 to N=2 . The designs were made in Matlab-Simulink environment and the simulations were run for 5000 samples for Gaussian noise and sine wave input, respective 12*104 samples in the case of speech input. A reverberating effect was added to the input by an artificial Schroeder I reverberator which contained four comb filters in parallel and two all-passes filters series connected. The first estimation of a system capability is represented by the (output error-voice input), but in order to measure its potential, Echo Return Loss Enhancement (ERLE) should be computed; it is defined as the ratio of the power of the desired signal over the power of the residual signal. Comparison between full band, sub bands, adaptive combination, and their improvement is done based on SNR and MSE and by using output error- voice input and ERLE.

6. Conclusion

The NSAF is a good candidate for implementing acoustic echo cancellers because of its fast convergence rate. However, it requires a tradeoff between fast convergence rate and small steady-state MSE. This paper presented an adaptive convex combination of two NSAFs to solve this problem. In addition to the conventional coupling update method for component filters, we also proposed a coupling update mechanism which requires less number of adaptive filters as than used in conventional method. To verify the effectiveness of the proposed scheme, simulations using different input signals as well as system noises with different SNRs were performed. The experimental results demonstrated that the proposed scheme can obtain improved performance as compared to the conventional NSAF.

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