Development of Partitioned Block Frequency Domain Adaptive Filter (PBFDAF) Approach for Prediction Error Method (PEM) Framework Using Double Talk- Robust Acoustic Echo Cancellation

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Abstract- In this paper, we propose a new framework to tackle the double-talk (DT) problem in acoustic echo cancellation (AEC). It is based on a frequency-domain adaptive filter (FDAF) implementation of the so-called prediction error method adaptive filtering using row operations (PEM-AFROW) leading to the FDAF-PEM-AFROW algorithm. We show that FDAF-PEM-AFROW is by construction related to the best linear unbiased estimate (BLUE) of the echo path. We depart from this framework to show an improvement in performance with respect to the adaptive filters minimizing the BLUE criterion, namely the PEM-AFROW and the FDAF-NLMS with near-end signal normalization. One of the contributions is to propose the instantaneous pseudo-correlation (IPC) measure between the near-end signal and the loudspeaker signal. The IPC measure serves as an indication of the effect to FADT situation occurring during adaptation. We motivate the choice of FDAF-PEM-AFROW over PEM-AFROW and FDAF-NLMS with near-end signal normalization, based on performance, computational complexity and related IPC measure values. Moreover, we use the FDAF-PEM-AFROW frame work to improve several state-of-the-art variable step-size (VSS) and variable regularization (VR) algorithms. The FDAF-PEM-AFROW versions significantly outperform the original versions in every simulation. In terms of computational complexity, the FDAF-PEM-AFROW versions are themselves about two orders of magnitude cheaper than the original versions.

Index Terms—Acoustic echo cancellation, double-talk-robust acoustic echo cancellation, double-talk, frequency-domain adaptive filters, prediction error method, and variable step size.

I. INTRODUCTION

Acoustic Echo Cancellation (AEC) is used in many speech communication applications where the existence of echoes degrades the speech intelligibility and listening comfort [1]. These applications range from mobile and hands-free telephony to teleconferencing and voice over IP (VoIP),

A far end speech signal u(t) is played back in an enclosure (i.e., the room) through a loud speaker. In the room there is a microphone to record a near-end speech signal, which is to be transmitted to the far-end side. laptops, etc. The typical set-up for an acoustic echo canceller is depicted in Fig.1.

An acoustic echo path between the loudspeaker and the microphone exists so that the microphone signal y(t) contains an undesired echo signal x(t) plus the near end signal v(t), i.e., y(t) = x(t) + v(t). The echo signal x(t) can be considered as the far-end speech or loudspeaker signal u(t) filtered by the echo path. An acoustic echo canceller seeks to cancel the echo signal component x(t) in the microphone signal y(t) ideally leading to an *echo-free* error signal e(t), which is then transmitted to the far-end side. This is done by subtracting an estimate of the echo signal $\hat{x}(t)$ from the microphone signal i.e., $e(t) = y(t) - \hat{x}(t)$. Standard approaches to AEC rely on the assumption that the echo path can be modeled by a linear FIR filter [2]–[4]. The coefficients of the echo path are collected in the parameter Vector

$f(t) = [f_0(t), f_1(t), , \ldots\ldots, f_{N-1}(t)]^T \in R^N$ such that

$x(t) = f^T(t)\, u(t) = F(q, t)\, u(t)$

where $u(t) = [u(t), u(t-1), \ldots, u(t- N + 1)]^T$

and $F(q, t) = f_0(t) + f_1(t)q^{-1} + \ldots + f_{N-1}(t)q^{N-1}$ with q^{-1} the unit delay operator, i.e., $q^{-1}u(t) = u(t-1)$.

An adaptive filter of sufficient order is used to provide an estimate

$\hat{f}(t) = [\hat{f}_0(t), \hat{f}_1(t), \ldots, \hat{f}_{N-1}(t)]^T \in R^N$ of f, such that the echo signal estimate is
$\hat{x}(t) = \hat{f}^T(t)u(t) = \hat{F}(q,t)u(t)$
with $\hat{F}(q,t) = \hat{f}_0(t) + \hat{f}_1(t)q^{-1} + \ldots + \hat{f}_{N-1}(t)q^{N-1}$.

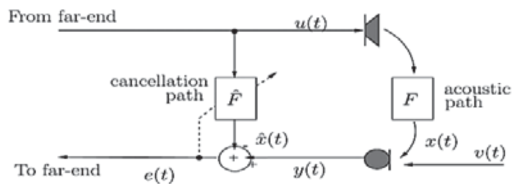


Fig.1. Typical set-up for AEC.

Practical AEC implementations often rely on computationally simple time-domain stochastic gradient algorithms, such as the least mean squares (LMS) algorithm [5], the normalized LMS(NLMS) algorithm[3],or affine projection algorithm (APA) [12], which are very sensitive to the presence of a near-end signal [2]. In general, the presence of a near-end signal, in a so-called double-talk (DT) scenario, makes the AEC adaptive filter converge slowly or even diverge. There are several approaches to tackle the problem of DT in AEC. We give a brief explanation of five different approaches: two that are based on a *variable step size* (VSS), one based on a *variable regularization* (VR) and two based on a *best linear unbiased estimate* (BLUE) of the echo path.

The first approach is based on the so-called gradient-based VSS algorithms [6]–[11]. From this class of algorithms, the only one specifically designed for DT-robust AEC is the *projection correlation* VSS (PCVSS), which has been proposed in [11]. PCVSS is based on the APA, and so will be referred to as PCVSS-APA. In PCVSS-APA, the adaptation rate is controlled by a measure of the correlation between instantaneous and long-term averages of the so-called *projection vectors* i.e., gradient vectors in APA.

The second approach is based on the *non-parametric* VSS (NPVSS) algorithm proposed in [13].Different NPVSS-based algorithms have been developed and applied for DT-robust AEC when updated with the NLMS algorithm, e.g.,[14]and [15].To increase their convergence speed, an APA version of these algorithms has been proposed, resulting in the *practical* VSS affine projection algorithm(PVSS-APA)[16].

The third approach is based on equipping the adaptive filter with a VR. Several VR algorithms have been proposed in the literature based on the derivation of an optimal regularization parameter, which sometimes need quantities or models that are difficult to obtain in practice[17],[18].Practical implementations of these algorithms have also been proposed that employ more easily measurable quantities. One example is the APA-based VR (VR-APA) algorithm that has been proposed in [19], which incorporate the statistics of the noise into the design of the VR.

The fourth approach is based on a minimum-variance echo path estimate, i.e., the BLUE [20]. This estimate depends on the near-end signal characteristics, which are in practice unknown and time-varying [2],[21]. One approach to achieve the BLUE is based on the prediction error method (PEM) [22] for jointly estimating the echo path model and an auto-regressive (AR) model of the near-end signal. The algorithms in [2],[21]aim to whiten the near-end signal component in the microphone signal by using adaptive de-correlation pre-filters that are estimated concurrently with the echo path. Among the PEM-based algorithms, the PEM adaptive filtering using row operations (PEM-AFROW)[23] is particularly interesting and it will be explained further on. Other algorithms, although not applied to DT-robust AEC, have been proposed for recursively minimizing the BLUE criterion. In fact, in [24], [25], a frequency-domain adaptive filtering (FDAF) algorithm has been obtained by first minimizing the BLUE criterion using a time-domain block stochastic gradient algorithm and then switching to the frequency domain to reduce the computational complexity. One advantage of frequency-domain adaptive filtering compared to time-domain adaptive filtering is that the step size can be normalized independently for each frequency bin. Including such normalization in the adaptive filter update equation results in a more uniform convergence over the entire frequency range. In the equal, the standard frequency-domain adaptive filtering [34] is referred to as FDAF-NLMS, i.e., an FDAF with a loudspeaker signal normalization factor. The algorithm proposed in [24] is therefore referred to as FDAF-NLMS *with near-end signal normalization*. The PEM-based and FDAF-based approach to achieve the BLUE will be explained further on.

One particular assumption in all these algorithms and inmost AEC applications in general, is that the near-end signal is uncorrelated with the loudspeaker signal. This assumption can truly be exploited only for infinitely long observations of ergodic and stationary processes [3].In real AEC applications, however, the near-end signal as well as the loudspeaker signal is a speech signal that is highly colored and non-stationary. Even when the near-end signal and the loudspeaker signal are assumed to be un- correlated, this however does not imply that the correlation between these two signals is zero within a short-time observation window [30]. Hence, one of the contributions of this paper is to derive and define the *instantaneous pseudo-correlation* (IPC) measure between the near end signal v(t) and the loudspeaker signal u(t). The IPC measure serves as an indication of the effect of a DT situation occurring during adaptation, as it will be explained.

The aim of this paper is to introduce a new frame work for DT-robust AEC, which is based on an FDAF implementation of the PEM-AFROW (FDAF-PEM-AFROW). We depart from this framework to show an improvement in performance with respect to PEM-AFROW and FDAF with near-end signal normalization. Although these three algorithms are related to the BLUE, we show that FDAF-PEM-AFROW is the preferred choice for DT-robust AEC. We motivate the choice of FDAF-PEM-AFROW over PEM-AFROW and FDAF-NLMS with near-end signal normalization, based on performance improvement, computational complexity reduction and lower IPC measure values. Moreover, we use the FDAF-PEM-AFROW framework to improve the previously introduced VR-APA, PVSS-APA and PCVSS-APA leading to the VR-FDAF-PEM-AFROW, PCVSS-FDAF-PEM-AFROW and PCVSS-FDAF-PEM-AFROW respectively. The FDAF-PEM-AFROW versions significantly reduce the computationally complexity and improve the performance of the original versions in every simulation.

The paper is organized as follows. In Section II, the BLUE is explained in two subsections: in Section II-A, the basic linear regression model is reviewed, including unbiased constraints that are assumed in the derivation of typical algorithms for AEC. In Section II-B, the generalized least squares model is reviewed, which provides a framework to explain other related estimators. In Section III-A, the BLUE achieved using the PEM is considered and in Section III-B, the BLUE achieved using the FDAF-NLMS with near-end signal normalization is considered. In Section IV, the IPC measure is derived and defined, and several simulation results are shown evaluating the IPC measure in the NLMS and the FDAF-NLMS. The recursions that are used to compute the IPC measure are given in Appendix A. In Section V, the proposed FDAF-PEM-AFROW is derived. In Section VI, computer simulations are provided. In Section VI-A, we motivate the choice of the FDAF-PEM-AFROW algorithm over PEM-AFROW and FDAF-NLMS with near-end signal normalization, based on performance improvement, computational complexity reduction and lower IPC measure values. In Section VI-B more detail is provided about the selected state-of-the-art VSS and VR algorithms as well as an explanation of their FDAF-PEM-AFROW versions. Simulation results are provided with a complexity analysis comparing the following algorithms: PVSS-APA, PCVSS-APA, VR-APA, PVSS-FDAF-PEM-AFROW, PCVSS-FDAF-PEM-AFROW and VR-FDAF-PEM-AFROW. Finally, Section VII concludes the paper.

II. BEST LINEAR UNBIASED ESTIMATE

A. Linear Unbiased Estimator

$$y = Xf + v \quad (1)$$

Where

$$y = [y(1), y(2), \dots\dots\dots, y(L)]^T \quad (2)$$

$$v = [v(1), v(2), \dots\dots\dots, v(L)]^T \quad (3)$$

$$X = [u(1), u(2), \dots\dots\dots, u(L)]^T \quad (4)$$

$$\hat{f} = D^T y \quad (5)$$

$$D^T X = I_N \quad (6)$$

$$\varepsilon\{D^T v\} = 0_{N \times 1} \quad (7)$$

B. Generalized Least Squares and BLUE

$$\hat{f} = [X^T M^{-1} X]^{-1} X^T M^{-1} y \quad (8)$$

$$M_{BLUE} = R_v = \varepsilon\{v v^T\} \quad (9)$$

$$\widehat{f_{BLUE}} = [X^T R_v^{-1} X]^{-1} X^T R_v^{-1} y \quad (10)$$

$$\hat{\mathbf{f}}_{LS} = [X^T X]^{-1} X^T y \qquad (11)$$

III.THE BLUE IN ADAPTIVE FILTERING ALGORITHMS

It has been shown [21] that the BLUE can be considered an optimal acoustic echo path estimate during DT. However, calculating the BLUE in an AEC framework is problematic due to its dependence on the near-end signal covariance matrix R_v. Therefore, we will seek a signal transformation that diagonalizes R_v and include an estimation of the resulting diagonal elements in the proposed adaptive filtering algorithm. PEM-based algorithms, which have been proposed in [2],[21], provide a signal-dependent way of diagonalizing R_v, which requires the estimation of a near-end signal model. On the other hand, FDAF-based algorithms, which have been proposed in [24],[25] are capable of diagonalizing R_v in a signal independent way, after some matrix manipulation, and thus provide an attractive alternative to the PEM-based algorithms.

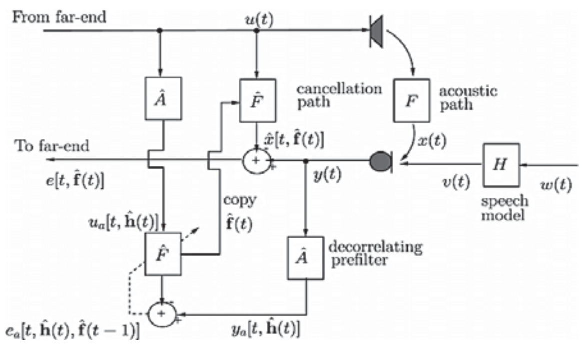


Fig. 2. Typical set-up for AEC using a decorrelation pre-filter.

A. PEM BASED BLUE

Note that the BLUE as in (10) usually cannot be calculated as such, because the autocorrelation matrix R_v is generally unknown. Therefore, R_v will be conveniently transformed. Let us first assume that the near-end signal is generated as $v(t) = H(q,t)w(t)$ where $w(t)$ is a white noise excitation signal with variance $\sigma_w(t)$, i.e., $\varepsilon\{w(t)w(t-i)\} = \delta(i)\sigma_w^2(t)$, and

$$H(q,t) = \frac{1}{A(q,t)} = \frac{1}{1 - a_1(t)q^{-1} - \dots - a_{n_A}(t)q^{-nA}} \qquad (12)$$

$$M_{PEM} = \varepsilon\{H(q) w\, w^T H^T(q)\} \qquad (13)$$

$$\hat{f}_{BLUE} = \Gamma^{-1}\psi \qquad (14)$$

Where

$$\Gamma = (H^{-1}(q)\, X)^T W_{PEM}^{-1} (H^{-1}(q)\, X) \qquad (15)$$

$$\Psi = (H^{-1}(q) X)^T W_{PEM}^{-1} (H^{-1}(q)\, y) \qquad (16)$$

With

$$W_{PEM} = \begin{bmatrix} \sigma_w^2(1) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_w^2(L) \end{bmatrix} \qquad (17)$$

Which corresponds to a pre-filtering and weighting of the t^{th} row, t = 1,….,L of X and with the inverse near-end signal model $H^{-1}(q,t) = A(q,t)$ and the inverse excitation signal variance $\sigma_w^{-1}(t)$.

In practice, also (near-end) noise will be present in the microphone signal. Although, noise has not been included in the model for deriving the algorithm, it will be included in the simulation section. The PEM-based approach achieving the BLUE leads to very simple time-domain stochastic gradient algorithms that feature two components (asshowninFig.2):(1) a whitening of the near-end signal component in the microphone signal by using estimated de-correlation pre-filters $\hat{A}(t)$, (2) a single weighting scalar in the denominator of the adaptive filter update equation using the estimated excitation signal variance.

[21], it has been shown that PEM-based algorithms that achieve the BLUE, are possible if three conditions are fulfilled, (1)the near-end signal v(t) can at each time instant be modeled as an AR process of order n_A (2) the prefilter $\hat{A}$(q,t) contains at each time instant the true AR coefficients, i.e., $\hat{A}$(q,t) = A(q,t) and(3) the weighting scalar in the denominator of the adaptive filter update equation $\hat{\sigma}_w(t)$ is at each time instant equal to the true variance of the near-end excitation signal w(t), i.e., $\hat{\sigma}_w(t) = \sigma(t)$. However, it seems that some of the previous conditions are difficult to fulfill in practice. In this case, the complete whitening of the near-end signal will not be achieved (i.e., W_{PEM} will not be diagonal) and, therefore, the use of a single weighting scalar $\hat{\sigma}_w(t)$ in the denominator of the adaptive filter update equation will not be possible. Even if the near-end signal autocorrelation matrix R_v could be estimated as such, its direct inversion, as needed in a typical time-domain stochastic gradient algorithm, would be prohibitive in terms of computational complexity.

B. FDAF-Based BLUE

In this section, we explain how in [24] an FDAF-based algorithm has been obtained by first minimizing the BLUE criterion using a time-domain blocks stochastic gradient algorithm and then switching to the frequency domain to reduce the computational complexity. To this end, consider the cost function

$$J_{BLUE}(f) = (Xf - y)^T R_v^{-1}(Xf - y) \qquad (18)$$

from which the BLUE in(10) is actually obtained. Following [24] and [25], a time domain block stochastic gradient algorithm minimizing (18) can be derived. In [24]–[26] and [29] it has been shown how FDAF-based algorithms can then be derived by rewriting a time-domain blocks stochastic gradient algorithm in a way that Toeplitz and circulated matrices are explicitly shown. It is important to recognize that the Toeplitz property of R_v is a direct consequence of the assumption that the vector v, is wide sense stationary [3].

Similar to[26],[29],in [24],[25]a Toeplitz matrix is diagonalizes in two steps: (1) a Toeplitz matrix is transformed into a circulator matrix and(2) a circulator matrix is transformed into a diagonal matrix using the DFT. In the resulting diagonal matrix, the different diagonal elements correspond to the near-end signal variance in different frequency bins. In FDAF-based algorithms, the near-end signal variance in each frequency bin can be straight forwardly incorporated as a normalization factor in the adaptive filter update equation. Indeed, in [24], and [25], it has been shown that such a normalization can significantly improve the performance of an FDAF-NLMS. The algorithm proposed in [24] is therefore referred to as FDAF-NLMS with near-end signal normalization. In [24] and [25], only a stationary colored near-end noise signal is considered and the near-end noise signal variance in each frequency bin is then directly estimated from the error signal e(t).

IV. INSTANTANEOUS PSEUDO-CORRELATION MEASURE

The unbiased constraints in (6), (7) must be satisfied in both the PEM-based and FDAF-based BLUE. Since Din (7) is a function of the loudspeaker signal matrix X, the constraint reduces to $\varepsilon\{X^T v\} = 0_{Nx1}$.This means that the near-end signal should be uncorrelated with the loudspeaker signal. This assumption can truly be exploited only for infinitely long observations of ergodic and stationary processes [3]. In real AEC applications, however, the near-end signal as well as the loudspeaker signal is a speech signal that is highly colored and non-stationary. Even when the near-end signal and the loudspeaker signal are assumed to be uncorrelated, this however does not imply that the correlation between these two signals is zero within a short-time observation window [30].

It is known [32] that the correlation between these two signals causes standard adaptive filtering algorithms to converge to a *biased* solution. This means that the adaptive filter does not only predict and cancel the echo signal component in the microphone signal, but also part of the near-end signal. To analyze this, we derive and define the *instantaneous pseudo-correlation* (IPC) measure between the near-end signal v(t) and the loudspeaker signal u(t). It should be clear that the IPC measure is a performance measure used in simulations; hence every signal is needed separately.

To this end, we first consider the time-domain LMS algorithm update equation given as

$$e(t) = y(t) - \hat{f}^T(t-1)u(t) \qquad (19)$$

$$\hat{f}(t) = \hat{f}(t-1) + \mu e(t)u(t) \qquad (20)$$

$$\hat{f}(t-1) = \mu \sum_{i=0}^{t-1} e(i)u(i) \qquad (21)$$

So that

$$e(t) = y(t) - \mu \sum_{i=0}^{t-1} e(i)(u^T(i)u(t)) \qquad (22)$$

Where $y(t) = x(t) + v(t)$,

$$e_x(t) = x(t) - \mu \sum_{i=1}^{t-1} e_x(i)\left(u^T(i)u(t)\right) \quad (23)$$

$$e_v(t) = e(t) - e_x(t)$$

$$= y(t) - x(t) - \mu \sum_{i=1}^{t-1} \left(e(i) - e_x(i)\right)\left(u^T(i)u(t)\right)$$

$$= v(t) - \mu \sum_{i=1}^{t-1} e_v(i)\left(u^T(i)u(t)\right), \quad (24)$$

$$\mu \sum_{i=1}^{t-1} e_v(i)\left(u^T(i)u(t)\right) = 0 \quad (25)$$

$$z(t) = \frac{\mu}{N} \sum_{i=1}^{t-1} e_v(i)\left(u^T(i)u(t)\right) = \frac{\mu}{N} \hat{f}^T(t-1)u(t), \quad (26)$$

i.e., the estimated variance of the signal z (t) normalized w.r.t. the estimated variance of the near-end signal with L the total length of the signals. The normalization makes the IPC measure independent of the level of the near-end signal. In what follows, we show that within their adaptation loops the NLMS and the FDAF-NLMS show different values of the IPC measure.

IPC Measure in PEM-AFROW-Based Algorithms: Table III shows the values of the IPC measure (27) for the PEM-AFROW and the proposed FDAF-PEM-AFROW. This is to show the impact that either the pre-filter or the type of adaptation (i.e., time- domain or frequency-domain) has on the resulting IPC measure. The IPC measure is calculated without using the near-end signal variance estimate. Calculations are performed in the same scenario as before with N = 1001 and two different model orders n_A= 1 to n_A= 12. The recursions for computing z (t) in PEM-based algorithms are given in Appendix A.

To conclude, comparing Table I to Table III it seems that the IPC measure in the time-domain NLMS is higher than that of the time-domain PEM-AFROW. The reason appears to be that PEM-AFROW includes a pre-filtering operation. However, the IPC measure in PEM-AFROW is higher than that of FDAF-NLMS. The reason is that FDAF-NLMS is implemented in the frequency domain, which seems to reduce the IPC measure as seen in Fig.3. Finally and gathering both a prefilter and a frequency-domain implementation, the FDAF-PEM-AFROW has the lowest IPC measure of all. Although the three algorithms are constructed from the BLUE framework and should therefore obtain the minimum variance echo path estimate during DT, it turns out that the differences between them are clear (as shown in Fig. 4). In the PEM-AFROW, it is clear that fulfilling the three conditions to achieve the BLUE in practice is very difficult. This fact seems to affect the time-domain PEM-AFROW much more than the FDAF-PEM-AFROW.

B. Results from VSS Algorithms

In this section, we explain the proposed FDAF-PEM- AFROW versions of three state-of-the-art algorithms: variable regularization (VR-APA) [19], practical variable step size (PVSS-APA) [16], projection-correlation variable step size (PCVSS-APA) [11]. It is important to notice that the FDAF-PEM-AFROW given in Algorithm1 uses the inverse of the estimated variance of the near-end excitation signal w(t), to account for the variance in the estimation so as to obtain the BLUE of the echo path. $\hat{\sigma}_w(t)$ is estimated directly using the Levinson-Durbin algorithm and is subsequently used in the adaptation gain G(m, k). On the other hand, in the PVSS-APA [16] and VR-APA [19] the near-end signal variance $\sigma_v(t)$ needs to be estimated instead.

The three selected VSS algorithms are implemented using FDAF-PEM-AFROW and show different levels of improvement as compared to the original versions using APA with projection order K = 4. In Fig.5, the upper part shows the microphone signal contributions where the dark solid line is the echo and the light green is the near-end signal. In Fig.6 (a) and Fig.6 (b) the upper part shows the full-length simulation and the bottom parts how a zoom-in is coinciding with the DT situation. In the references to the original versions, a deep explanation of the original algorithms, and the effect to the main parameters on the adaptation, is given. In the FDAF-PEM-AFROW versions, the most important parameter is the step size, which controls the convergence speed. The other parameters are mostly used to fine-tune the smoothness of the curve. In every simulation we use the parameters, N = 1001, n_A= 1, P =160.

VR-FDAF-PEM-AFROW (Algorithm2):

In[19], a practical algorithm to design a VR factor for the APA has been proposed. The condition to derive the VR-APA is to minimize the difference between the estimated and true filter coefficients. For this, it is assumed that the l_2 norm of the *a posteriori* error is equal to the near-end noise signal variance, similar to the condition imposed in [13], [16]. The VR-APA performance has been compared to the performance of existing techniques [17], [18], [35], demonstrating the effectiveness of VR-APA. The implementation of the VR-FDAF-PEM-AFROW is straight forward since the estimate of the near-end excitation signal variance is calculated using the Levinson-Durbin algorithm. The VR parameter is obtained in *line*8 and included in the normalization factor in *line*9 as shown in Algorithm 2. In this particular case, the performance of VR-APA, shown in Fig.5, is very poor. The algorithm is difficult to tune such that it has a comparable initial convergence curve as the VR-FDAF-PEM-AFROW. On the other hand, it is obvious that VR-FDAF- PEM-AFROW significantly out performs VR-APA, turning the latter into an algorithm suitable for DT situations as well.

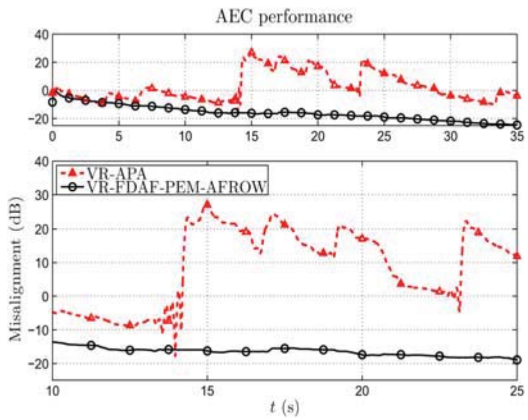
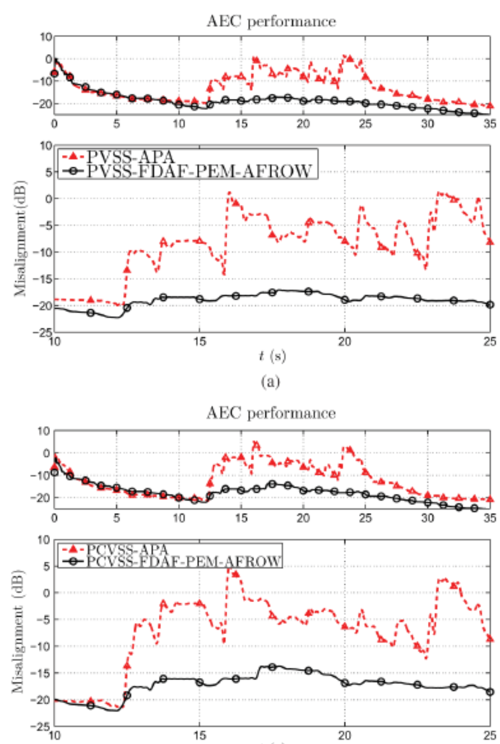


Fig.3. AEC performance using speech signals (far end and near-end) between 12.5and25s.



(b)

Fig. 4. AEC performance using speech signals (far-end and near-end) between 12.5 and 25 s. The original APA and the FDAF-PEM-AFROW versions are compared when bursting DT occurs at 10 dB SER and white near-end noise at 30 dB SNR. In (a) and (b)

The original APA and the FDAF-PEM AFROW version of variable regularization are compared when bursting DT occurs at 10dB SER and white near-end noise at 30dB SNR. The upper part shows the microphone signal contributions where the dark solid line is the echo and the light green is the near-end signal. The convergence of PVSS-FDAF-PEM-AFROW, shown in Fig.6 (a), is similar to the convergence for the PVSS-APA. During DT PVSS-FDAF-PEM-AFROW clearly out performs PVSS-APA.

C. Complexity Analysis

The complexity analysis in Table IV shows that, for a typical choice of the algorithm parameters, the FDAF-PEM-AFROW algorithms are about two order so magnitude cheaper than the corresponding original algorithms. Hence, it is concluded that the PVSS-FDAF-PEM-AFROW, PCVSS-FDAF-PEM- AFROW and VR-FDAF-PEM-AFROW algorithms are to variable step size(WVSS) and a gradient spectral variance smoothing (GSVS) for DT-robust AEC and for acoustic feedback cancellation(AFC). In their AEC simulations, the WVSS-GSVS-FDAF-PEM-AFROW algorithm has obtained robustness and smooth adaptation in highly adverse scenarios such as in bursting DT at high levels, and in a change of acoustic path during continuous DT using white as well as colored non-stationary near-end noise.

V. CONCLUSION

In this paper, we have proposed a new framework to tackle the problem of double-talk (DT) in acoustic echo cancellation (AEC). It is based on a frequency domain adaptive filtering (FDAF) implementation of the so-called PEM-AFROW algorithm (FDAF-PEM-AFROW). It has been shown that the FDAF-PEM-AFROW minimizes the BLUE criterion and so provides an optimal acoustic echo path estimate during DT. The FDAF-PEM-AFROW algorithm shows an improved performance with respect to the PEM-AFROW and FDAF-NLMS with near-end signal normalization. Although these three algorithms are constructed from the BLUE framework and should therefore obtain the minimum variance echo path estimate during DT, in practice clear differences between them are observed. In PEM-AFROW, it is clear that fulfilling the three conditions to achieve the BLUE in practice is very difficult. This fact affects the PEM-AFROW much more than the FDAF-PEM-AFROW. We have shown that the instantaneous pseudo-correlation (IPC) measure between the near-end signal and the loud speaker signal is significantly reduced when using the combination of FDAF and PEM, as done in FDAF-PEM-AFROW.

VI. ACKNOWLEDGEMENT

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