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A Class of Variable Step-Size NLMS and Affine Projection Algorithms Suitable for Echo Cancellation

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Abstract – The normalized least-mean-square (NLMS) algorithm and the affine projection algorithm (APA) are the most common choices for echo cancellation. In this type of application, an adaptive algorithm with a constant step-size has to compromise between several performance criteria (e.g., high convergence rate versus low misadjustment). In this paper we present a class of variable step-size NLMS and APAs, which are designed to recover the near-end signal in the error of the adaptive filter. The simulation results indicate a robust behaviour of these algorithms against different types of near-end signal variations, including double-talk.
Keywords: adaptive filtering, affine projection algorithm (APA), echo cancellation, normalize least-mean-square (NLMS), variable step-size.

I. INTRODUCTION

Echo cancellation is one of the most popular applications of adaptive filtering [1]. In both network and acoustic echo cancellation contexts, the basic solution is to build a model of the impulse response of the echo path using an adaptive filter, which provides at its output a replica of the echo. Even if the formulation is straightforward, several specific problems have to be addressed. First, the echo path can be extremely long and it may rapidly change during the connection. Secondly, the background noise that appears at the near-end side can be strong and non-stationary in nature. Third, the involved signals (i.e., mainly speech) are non-stationary and highly correlated. Finally, the behaviour during double-talk (i.e., the talkers on both sides speak simultaneously) has to be considered.

Even through various kinds of adaptive algorithms [2] are theoretically applicable for echo cancellation, in most cases a simple and robust algorithm outperforms more sophisticated solutions. Therefore, in many applications with limited precision and processing power, the normalized least-mean-square (NLMS) algorithm or the affine projection algorithm (APA) [3] are preferred. The performance of these algorithms is governed by the step-size parameter. This parameter has to be chosen based on a compromise between fast convergence rate and good tracking capabilities on the one hand, and low misadjustment on the other hand. In order to meet this conflicting requirement, a number of variable step-size NLMS (VSS-NLMS) algorithms and variable step-size APAs (VSS-APAs) were developed [4], [5] (and references therein). Nevertheless, most of these algorithms require the tuning of some parameters which are not a priori available or have to be estimated (e.g., background noise power). For real-world echo cancellation scenarios, it is highly desirable to use non-parametric algorithms, in the sense that no information about the environment is required.

A major aspect that has to be considered in echo cancellation concerns the behaviour during double-talk. In this case, the near-end speech signal acts like a large level of uncorrelated disturbance to the adaptive filter, and it may cause its divergence. For this reason, the standard procedure is to use a double-talk detector (DTD) in order to slow down or completely halt the adaptation process during double-talk periods. Nevertheless, there is some inherent delay in the decision of a DTD; during this small period a few undetected large amplitude samples can perturb the echo path estimate considerably. Consequently, it is highly desirable to improve the robustness of the adaptive algorithm in order to handle a certain amount of double-talk without diverging. This is the motivation behind the development of the so-called robust algorithms [6] (and references therein).

In this paper, we present a class of VSS-NLMS algorithms and VSS-APAs derived in the context of echo cancellation. The proposed approach takes into account the fact that the near-end signal contains the background noise or/and a speech sequence, and these signals should be recovered in the error signal of the adaptive filter. Consequently, these algorithms are robust to near-end signal variations like background noise increase or double-talk. The simulation results support the theoretical findings.

The paper is organized as follows. Section II introduces the basic idea of the proposed VSS-NLMS algorithms. The generalization of the approach for the case of VSS-APAs is developed in Section III. The simulation results are presented in Section IV. Finally, Section V concludes this work.

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II. A CLASS OF VSS-NLMS ALGORITHMS

A general system model for echo cancellation is depicted in Fig. 1. The goal of this scheme is to identify an unknown system (i.e., echo path) using an adaptive filter. We assume that both systems have finite impulse responses of length L, defined by the real-valued vectors $\mathbf{h} = [h_0\ h_1\ \ldots\ h_{L-1}]^T$ and $\hat{\mathbf{h}}(n) = [\hat{h}_0(n)\ \hat{h}_1(n)\ \ldots\ \hat{h}_{L-1}(n)]^T$, where superscript T denotes transposition and n is the time index. The signal $x(n)$ is the far-end speech which goes through the impulse response of the echo path, $\mathbf{h}$, resulting the echo signal, $y(n)$. This signal is added with the near-end signal $v(n)$, resulting the desired signal $d(n)$. The near-end signal can contain both the background noise, $w(n)$, and the near-end speech, $u(n)$. The output of the adaptive filter, $\hat{y}(n)$, provides a replica of the echo, which will be subtracted from the desired signal of the adaptive filter. The DTD block controls the algorithm behaviour during double-talk; nevertheless, the proposed algorithms will be derived without involving the DTD decision.

Using the previous notations we may define the a priori and a posteriori error signals as, respectively

$$e(n) = y(n) - \hat{\mathbf{h}}^T(n-1)\mathbf{x}(n) = \mathbf{x}^T(n)\left[\mathbf{h} - \hat{\mathbf{h}}(n-1)\right] + v(n) \tag{1}$$

$$\varepsilon(n) = y(n) - \hat{\mathbf{h}}^T(n)\mathbf{x}(n) = \mathbf{x}^T(n)\left[\mathbf{h} - \hat{\mathbf{h}}(n)\right] + v(n) \tag{2}$$

where $\mathbf{x}(n) = [x(n)\ x(n-1)\ \ldots\ x(n-L+1)]^T$. The update equation for the NLMS type algorithms is

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \mu(n)\mathbf{x}(n)e(n), \tag{3}$$

where $\mu(n)$ is a positive factor known as the step-size, which governs the stability, the convergence rate and the misadjustment of the algorithm. Replacing (3) in (2) and taking (1) into account, it will result that

$$\varepsilon(n) = e(n)\left[1 - \mu(n)\mathbf{x}^T(n)\mathbf{x}(n)\right]. \tag{4}$$

At a first glance, the contribution of the near-end signal does not appear explicitly in the above relation. So that, in order to derive an expression for the step-size parameter, we may impose to cancel the a posteriori error signal, i.e., $\varepsilon(n) = 0$, assuming that $e(n) \neq 0$. As a result, $\mu(n) = [\mathbf{x}^T(n)\mathbf{x}(n)]^{-1}$, which is the step size of the classical NLMS algorithm. In practice, a positive constant (usually smaller than 1) multiplies this step size to achieve a proper compromise between the convergence rate and the misadjustment [2]. We should note that this straightforward approach holds in the noise-free single-talk scenario [i.e., $w(n) = 0$, $u(n) = 0$]. If we impose to cancel the a posteriori error in the presence of the near-end signal, it results from (2) that

$$\mathbf{x}^T(n)[\mathbf{h} - \hat{\mathbf{h}}(n)] = -v(n) \neq 0 . \tag{5}$$

Hence, the adaptive filter estimate is biased. The proper condition is $\mathbf{x}^T(n)[\mathbf{h} - \hat{\mathbf{h}}(n)] = 0$, which leads to

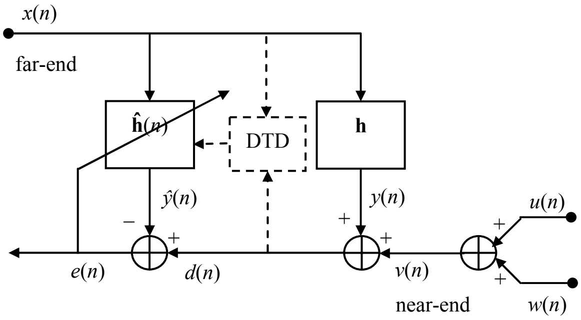

Fig. 1. System model for echo cancellation.

$$\varepsilon(n) = e(n)[1 - \mu(n)\mathbf{x}^T(n)\mathbf{x}(n)] = v(n). \tag{6}$$

Consequently, it can be imposed that $E\{\varepsilon^2(n)\} = E\{v^2(n)\}$ [5], where $E\{\bullet\}$ denotes the mathematical expectation. Squaring (6), then taking the expectations, and assuming that $\mathbf{x}^T(n)\mathbf{x}(n) = LE\{x^2(n)\}$ for $L >> 1$ (which is valid in the context of echo cancellation where the length of the adaptive filter is of the order of hundreds), it results that

$$E\{e^2(n)\}[1 - \mu(n)LE\{x^2(n)\}]^2 = E\{v^2(n)\}. \tag{7}$$

Regarding (7) as a quadratic equation, the solution for the step size parameter is

$$\mu(n) = \frac{1}{\mathbf{x}^T(n)\mathbf{x}(n)}\left[1 - \sqrt{\frac{E\{v^2(n)\}}{E\{e^2(n)\}}}\right]. \tag{8}$$

From a practical point of view, (8) has to be evaluated in terms of power estimates as

$$\mu(n) = \frac{1}{\mathbf{x}^T(n)\mathbf{x}(n)}\left[1 - \frac{\hat{\sigma}_v(n)}{\hat{\sigma}_e(n)}\right]. \tag{9}$$

In a general manner, the parameter $\hat{\sigma}_\alpha^2(n)$ denotes the power estimate of the sequence $\alpha(n)$, and can be computed as

$$\hat{\sigma}_\alpha^2(n) = \lambda\hat{\sigma}_\alpha^2(n-1) + (1-\lambda)\alpha^2(n), \tag{10}$$

where λ is a weighting factor chosen as $\lambda = 1 - 1/(KL)$, with $K > 1$. The initial value is $\hat{\sigma}_\alpha^2(0) = 0$.

Nevertheless, expression (9) is still useless in practice because it depends on a parameter that is unavailable, i.e., the near-end signal $v(n)$. Two main scenarios can be considered, as follows.

1) In the absence of the near-end speech, the near-end signal consists only of the background noise, $w(n)$. Its power can be estimated and it could be assumed constant, so that (9) becomes

$$\mu(n) = \frac{1}{\mathbf{x}^T(n)\mathbf{x}(n)}\left[1 - \frac{\hat{\sigma}_w}{\hat{\sigma}_e(n)}\right]. \tag{11}$$

This is the non-parametric VSS-NLMS (NPVSS-NLMS) algorithm proposed in [5]. Nevertheless, the background noise can be time-variant, so that the power of the background noise should be periodically estimated. Moreover, when the background noise changes between two consecutive estimations or during the near-end speech, its new power estimate will not be available immediately; consequently, until the next estimation period of the background noise, the algorithm behaviour will be disturbed.

2) In the double-talk case, the near-end signal $v(n)$ consists of both the background noise, $w(n)$, and the near-end speech, $u(n)$. It is very difficult to obtain an accurate estimate for the power of this combined signal, taking into account especially the non-stationary character of the speech signal. Therefore, (9) is still futile and the presence of a DTD is a must, in order to control the adaptation process during these periods.

In order to overcome these limitations, let us consider the previous cases in a more unified framework. The desired signal of the adaptive filter can be expressed as $d(n) = y(n) + v(n)$. Squaring this equation and taking the expectation of both sides [assuming that $y(n)$ and $v(n)$ are uncorrelated] it results that $E\{d^2(n)\} = E\{y^2(n)\} + E\{v^2(n)\}$. Assuming that the adaptive filter has converged to a certain degree, it can be considered that

$$E\left\{y^2(n)\right\} \cong E\left\{\hat{y}^2(n)\right\}. \quad (12)$$

Consequently, $E\{v^2(n)\} \cong E\{d^2(n)\} - E\{\hat{y}^2(n)\}$, or in terms of power estimates [similar to (10)]

$$\hat{\sigma}_v^2(n) \cong \hat{\sigma}_d^2(n) - \hat{\sigma}_{\hat{y}}^2(n). \quad (13)$$

For the case 1), when only the background noise is present, i.e., $v(n) = w(n)$, an estimate of its power is obtained using the right-hand term in (13). This expression holds even if the level of the background noise changes, so that there is no need for the estimation of this parameter during silences of the near-end speech. For the case 2), when the near-end speech is present (assuming that it is uncorrelated with the background noise), the near-end signal power estimate is expressed as $\hat{\sigma}_v^2(n) = \hat{\sigma}_w^2(n) + \hat{\sigma}_u^2(n)$; the last parameter denotes the power estimate of the near-end speech. Accordingly, the right-hand term in (13) provides a power estimate of the near-end signal. Most importantly, this term depends only on the signals that are available within the application, i.e., the desired signal, $d(n)$, and the output of the adaptive filter, $\hat{y}(n)$. Consequently, (9) can be rewritten as

$$\mu(n) = \frac{1}{\mathbf{x}^T(n)\mathbf{x}(n)}\left[1 - \frac{\sqrt{\hat{\sigma}_d^2(n) - \hat{\sigma}_{\hat{y}}^2(n)}}{\hat{\sigma}_e(n)}\right], \quad (14)$$

which is more suitable in practice [7], [8]. We refer this algorithm as VSS-NLMS-1. Another practical approach is to estimate the power of the near-end signal from the error signal $e(n)$, using a larger weighting factor as compared to (10), i.e.,

$$\hat{\sigma}_v^2(n) = \gamma\hat{\sigma}_v^2(n-1) + (1-\gamma)e^2(n), \quad (15)$$

with $\lambda < \gamma$ [9]. Then, the step-size is evaluated according to (9). We refer this algorithm as VSS-NLMS-2. Nevertheless, this algorithm is expected to be less robust against near-end signal variations as compared to the VSS-NLMS-1 algorithm.

All these VSS-NLMS algorithms are based on (9). Finnaly, a few practical issues have to be considered. First, in order to avoid divisions by small numbers, a positive constant δ, known as the regularization factor, needs to be added to the first denominator in (9). Also, a small positive number ξ should be added to the second denominator of (9) to avoid division by zero. Theoretically, we have $E\{e^2(n)\} \geq E\{v^2(n)\}$. Nevertheless, the estimates of these parameters could lead to some deviations from the previous theoretical condition, so that we will take the absolute value of the step-size parameter from (9).

III. GENERALIZATION IN THE VSS-APA CASE

The APA [3] is defined by the following relations:

$$\mathbf{e}(n) = \mathbf{d}(n) - \mathbf{X}^T(n)\hat{\mathbf{h}}(n-1), \quad (16)$$

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \mu\mathbf{X}(n)\left[\mathbf{X}^T(n)\mathbf{X}(n)\right]^{-1}\mathbf{e}(n), \quad (17)$$

where $\mathbf{e}(n)$ is the a priori error vector and $\mathbf{d}(n) = [d(n), d(n-1), \ldots, d(n-p+1)]^T$ is the desired signal vector of length p, with p denoting the projection order. The matrix $\mathbf{X}(n) = [\mathbf{x}(n), \mathbf{x}(n-1), \ldots, \mathbf{x}(n-p+1)]$ contains p input signal vectors and the constant μ denotes the step-size parameter of the algorithm.

Equation (17) can be rewritten in a different form as

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \mathbf{X}(n)\left[\mathbf{X}^T(n)\mathbf{X}(n)\right]^{-1}\boldsymbol{\mu}(n)\mathbf{e}(n) \quad (18)$$

where

$$\boldsymbol{\mu}(n) = \text{diag}\left\{\mu_0(n), \mu_1(n), \ldots, \mu_{p-1}(n)\right\} \quad (19)$$

is a p-by-p diagonal matrix. We can recover (17) imposing that $\mu_0(n) = \mu_1(n) = \ldots = \mu_{p-1}(n) = \mu$.

The a posteriori error vector can be defined using the adaptive filter coefficients at time n:

$$\boldsymbol{\varepsilon}(n) = \mathbf{d}(n) - \mathbf{X}^T(n)\hat{\mathbf{h}}(n). \quad (20)$$

Replacing (18) in (20) and taking (16) into account, it results that

$$\boldsymbol{\varepsilon}(n) = \left[\mathbf{I}_p - \boldsymbol{\mu}(n)\right]\mathbf{e}(n), \quad (21)$$

where $\mathbf{I}_p$ denotes a p-by-p identity matrix. The basic idea of the classical APA imposes to cancel p a posteriori errors, i.e., $\boldsymbol{\varepsilon}(n)=\mathbf{0}_{p\times 1}$, where $\mathbf{0}_{p\times 1}$ denotes a column vector with all its p elements equal to zeros. Assuming that $\mathbf{e}(n)\neq \mathbf{0}_{p\times 1}$, it results from (21) that $\boldsymbol{\mu}(n)=\mathbf{I}_p$. This corresponds to the classical APA update from (17), with the step-size $\mu = 1$. In the absence of the near-end signal (i.e., $v(n) = 0$, which leads to an ideal "system identification" configuration) the value of the step-size $\mu = 1$ makes sense, because it leads to the best performance [3].

Nevertheless, the echo cancellation scheme can be viewed as an "interference cancelling" configuration, aiming to recover an "useful" signal (i.e., the near-end signal) corrupted by an undesired perturbation (i.e., the echo); consequently, the "useful" signal should be recovered in the error signal of the adaptive filter. Therefore, a more reasonable condition is $\boldsymbol{\varepsilon}(n) = \mathbf{v}(n)$, where $\mathbf{v}(n) = [v(n), v(n-1), \ldots, v(n-p+1)]^T$ represents the near-end signal vector of length p. Taking (21) into account, it results that

$$\varepsilon_{l+1}(n)=\left[1-\mu_l(n)\right]e_{l+1}(n)=v(n-l), \qquad (22)$$

where $\varepsilon_{l+1}(n)$ and $e_{l+1}(n)$ denote the $(l+1)$-th elements of the vectors $\boldsymbol{\varepsilon}(n)$ and $\mathbf{e}(n)$, with $l=0,1,\ldots,p-1$. The expression of the step-size parameters $\mu_l(n)$ has to be found such that

$$E\left\{\varepsilon_{l+1}^2(n)\right\}=E\left\{v^2(n-l)\right\}. \qquad (23)$$

Squaring (22) and taking the expectations it results:

$$\left[1-\mu_l(n)\right]^2 E\left\{e_{l+1}^2(n)\right\}=E\left\{v^2(n-l)\right\}. \qquad (24)$$

By solving the quadratic equation (24), we obtain

$$\mu_l(n)=1-\sqrt{\frac{E\left\{v^2(n-l)\right\}}{E\left\{e_{l+1}^2(n)\right\}}}. \qquad (25)$$

or in terms of power estimates as [using (10)]

$$\mu_l(n)=1-\frac{\hat{\sigma}_v(n-l)}{\hat{\sigma}_{e_{l+1}}(n)}. \qquad (26)$$

The same scenarios from the Section II can be considered. Consequently, in case 1) will have

$$\mu_l(n)=1-\frac{\hat{\sigma}_w}{\hat{\sigma}_{e_{l+1}}(n)}. \qquad (27)$$

We refer this algorithm as the non-parametric VSS-APA (NPVSS-APA). For a value of the projection order $p = 1$, the NPVSS-NLMS algorithm from [5] is obtained. In the case 2), following a similar analysis as in Section II, it results

$$\mu_l(n)=1-\frac{\sqrt{\hat{\sigma}_d^2(n-l)-\hat{\sigma}_{\hat{y}}^2(n-l)}}{\hat{\sigma}_{e_{l+1}}(n)}. \qquad (28)$$

We refer this algorithm as VSS-APA-1. For $p = 1$, the VSS-NLMS-1 from Section II is obtained. Also, if we estimate the nominator from (26) using (15), it results another version of the algorithm, i.e., VSS-APA-2. (when $p = 1$, the VSS-NLMS-2 from Section II is obtained).

In all the cases, the adaptive filter coefficients should be updated according to (18), using the step-sizes from (19). In practice, (18) has to be rewritten as

$$\hat{\mathbf{h}}(n)=\hat{\mathbf{h}}(n-1)+\mathbf{X}(n)\left[\delta\mathbf{I}_p+\mathbf{X}^T(n)\mathbf{X}(n)\right]^{-1}\boldsymbol{\mu}(n)\mathbf{e}(n) \qquad (29)$$

where δ is the regularization factor. An insightful analysis about this factor, in the framework of APA, can be found in [10]. From practical reasons, the small positive number ξ should be added to the denominator of $\mu_l(n)$ to avoid division by zero. Also, as was discussed in the end of Section II, we will take the absolute value of these step-size parameters.

IV. SIMULATION RESULTS

The simulations were performed in the context of acoustic echo cancellation. The measured acoustic impulse response has $L = 512$ coefficients; the same length is used for the adaptive filter. The far-end signal $x(n)$ is a speech sequence. An independent white Gaussian noise signal $w(n)$ is added to the echo signal $y(n)$, with 20 dB signal-to-noise ratio (SNR). The performance is evaluated in terms of the normalized misalignment (in dB), defined as $20\log_{10}(\|\mathbf{h}-\hat{\mathbf{h}}(n)\|/\|\mathbf{h}\|)$, where $\|\bullet\|$ denotes the l_2 norm. For comparison purpose, an "ideal" VSS-NLMS (VSS-NLMS-id) algorithm and an "ideal" VSS-APA (VSS-APA-id) are considered in the simulations. They are based on the assumption that the near-end signal $v(n)$ is available (of course, this is not true in practice); its power estimate [which is evaluated using (10)] is introduced in (9) and (26).

The first set of simulations is performed in a single-talk case [i.e., $u(n) = 0$]. In Fig. 1, the VSS-NLMS algorithms are compared with the NLMS algorithm using the step-size $\mu(n) = 0.2[\delta + \mathbf{x}^T(n)\mathbf{x}(n)]^{-1}$ (this value compromises between convergence rate and misadjustment). The regularization factor for all the algorithms is $\delta = 20\sigma_x^2$, where σ_x^2 is the power of the input signal. The weighting factor from (10) is $\lambda = 1 - 1/6L$ and the parameter from (15) is $\gamma = 1 - 1/18L$. We assumed that the power of the background noise, σ_w^2, is known for the NPVSS-NLMS algorithm. It can be noticed from Fig. 1 that the VSS-NLMS-id algorithm outperforms the NLMS algorithm in terms of both convergence rate and misalignment. The performance of the NPVSS-NLMS algorithm is similar with the "ideal" algorithm. The VSS-NLMS-1 and VSS-NLMS-2 algorithms have a slower convergence rate.

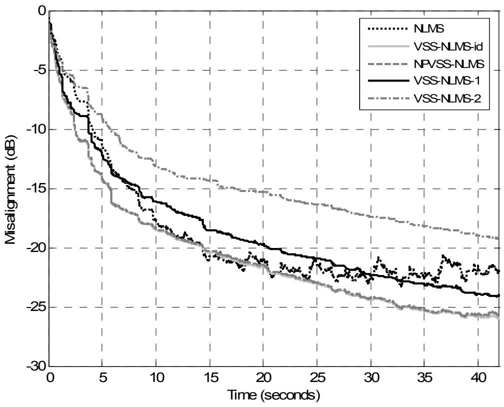

Fig. 1. Performance of the NLMS algorithms in the single-talk case.

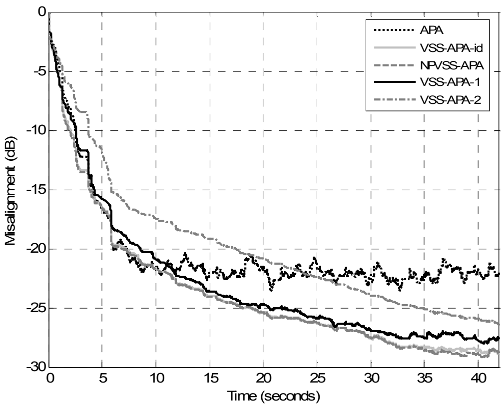

Fig. 2. Performance of the APAs in the single-talk case.

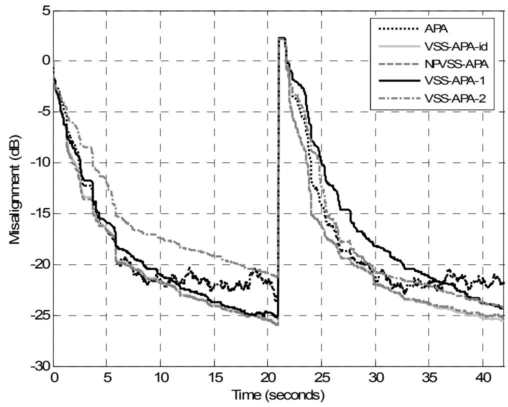

Fig. 3. Performance of the APAs in the single-talk case, when there is an abrupt change of the echo path.

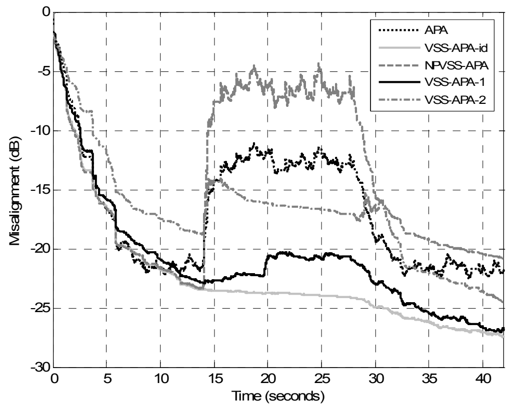

Fig. 4. Performance of the APAs in the single-talk case, when there is an increase of the backgroud noise.

In the case of the VSS-NLMS-1 algorithm, this is due to the assumption (12), which is not fulfilled in the first part of the algorithm. The convergence rate of the VSS-NLMS-2 algorithm is influenced by the value of γ. A larger value of this parameter speeds up the initial convergence but it is not proper from the robustness point of view.

The same experiment is repeted in Fig. 2 in the case of APAs. The VSS-APAs are compared with the classical APA using μ = 0.2, in the case of the projection order p = 2. The regularization factor for all the algorithms is $\delta = 50\sigma_x^2$. As expected, the convergence rates of APAs are improved as compared to the case of the NLMS algorithms. The VSS-APA-1 and VSS-APA-2 achieve a significant gain from this point of view. The performance of the VSS-APA-2 is very close to the "ideal" case.

An abrupt change of the acoustic echo path is considered in Fig. 3, in the case of APAs. The acoustic impulse response was shifted to the right by 12 samples after 21 seconds from the debut of the adaptive process. As expected, the VSS-APA-2 algorithm has a slower tracking reaction as compared to the other algorithms, since the assumption (12) is strongly biased in this situation. Nevertheless, the tracking capabilities of the VSS-APA-2 are improved for larger values of the projection order. As the value of the projection order of the APA becomes larger, the condition number of the matrix $\mathbf{X}^T(n)\mathbf{X}(n)$ also grows; consequently, a higher value of δ is required [10].

An increase of the background noise is experienced in Fig. 4. In this scenario, the SNR decreases from 20 dB to 10 dB after 14 seconds from the debut of the adaptive process, for a period of 14 seconds. It is assumed that the new background noise power estimate is not available for the NPVSS-APA. It can be noticed that the VSS-APA-1 and the VSS-APA-2 are more robust against the background noise variation, and they outperform the classical APA and the NPVSS-APA.

A second set of simulations is performed in a double-talk scenario. The near-end speech appears after 14 seconds from the debut of the adaptive process, for a period of 9.2 seconds. The results from Figs. 5 and 6 are obtained without using any DTD. It can be noticed that the VSS-NLMS-2 algorithm (Fig. 5) and VSS-APA-2 (Fig. 6) outperform by far their counterparts. In practice, a DTD can be involved in order to enhance the performance of these algorithms during double-talk periods. In Figs. 7 and 8, the previous experiment is repeated using a simple Geigel DTD [11]. It can be noticed that the performances of the VSS-NLMS-2 algorithm (Fig. 7) and VSS-APA-2 (Fig. 8) are improved as compared to the previous case. The other NLMS algorithms and APAs can not be "saved" by this procedure; they requires more complex DTDs, e.g., [12]. The presence of the DTD does not influence the performances of the "ideal" algorithms.

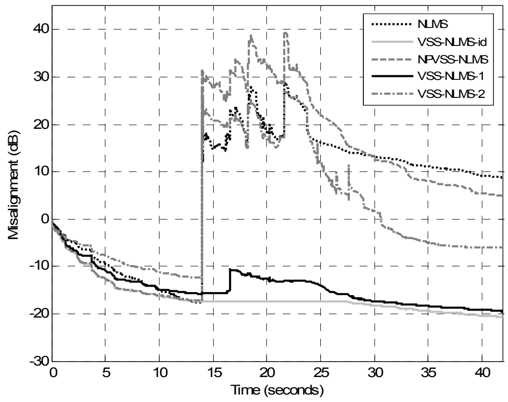

Fig. 5. Performance of the NLMS algorithms in the double-talk case, without DTD.

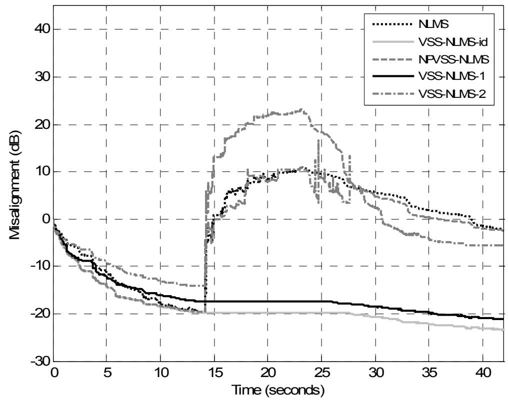

Fig. 7. Performance of the NLMS algorithms in the double-talk case, with Geigel DTD.

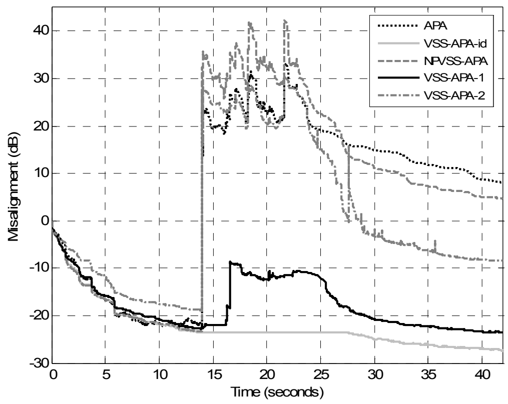

Fig. 6. Performance of the APAs in the double-talk case, without DTD.

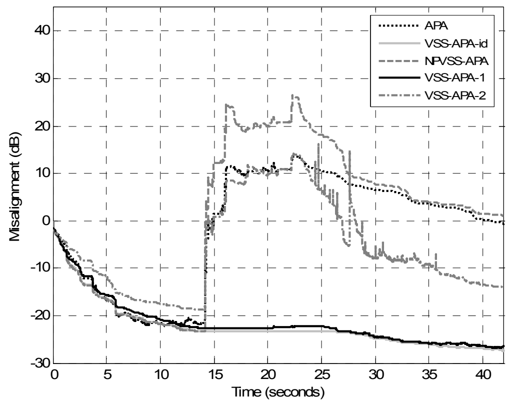

Fig. 8. Performance of the APAs in the double-talk case, with Geigel DTD.

V. CONCLUSIONS

A class of VSS-NLMS algorithms and VSS-APAs was presented in this paper. They are designed in the context of echo cancellation, in order to recover the near-end signal in the error of the adaptive filter. Consequently, they take into account the existence and the non-stationarity of the near-end signal. The variable step-size formula of the proposed algorithms resulted in a unified manner. The simulation results performed in an acoustic echo cancellation context sustain the theoretical findings. These algorithms were found to be more robust against near-end signal variations, like the increase of the background noise or double-talk. Concerning the last scenario, they can be combined with a simple Geigel DTD in order to enhance the overall performances.

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