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Noise cancellation in Speech Signals by Using a Constrained Stability LMS Algorithm

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ABSTRACT:

In this paper, we propose a novel least-mean-square (LMS) algorithm for filtering speech sounds in the adaptive noise cancellation (ANC) problem. It is based on the minimization of the squared Euclidean norm of the difference weight vector under a stability constraint defined over the a posteriori estimation error. To this purpose, the Lagrangian methodology has been used in order to propose a nonlinear adaptation rule which is derived from NLMS. The proposed method yields better tracking ability in this context as shown in the experiments which are carried out on the AURORA 2 and 3 speech databases. They provide an extensive performance evaluation along with an exhaustive comparison to standard LMS algorithms with almost the same computational load, including the LMS and other recently reported LMS algorithms such as the TV-LMS and NLMS. This algorithm can efficiently reduce the amount of missadjustment with respect to the optimum response than the previous LMS.

Index Terms— Adaptive noise canceller, least-mean-square (LMS) algorithm, speech enhancement, stability constraint.

I. INTRODUCTION

THE widely used least-mean-square (LMS) algorithm has been successfully applied to many filtering applications, including signal modeling, equalization, control, echo cancellation, biomedicine, or beam forming [1]. The typical noise cancellation scheme is shown in Fig. 1. Two distant microphones are needed for such application to capture the nature of the noise and the speech sound simultaneously. The correlation between the additive noise that corrupts the clean speech (primary signal) and the random noise in the reference input (adaptive filter input) is necessary to adaptively cancel the noise of the primary signal. The adjustable weights are typically determined by the LMS algorithm [1] because of its simplicity, ease of implementation and low computational complexity. The weight update equation for the adaptive noise canceller (ANC) is

$$\omega(n+1) = \omega(n) + \mu\, e^{*}(n)x(n) \qquad (1)$$

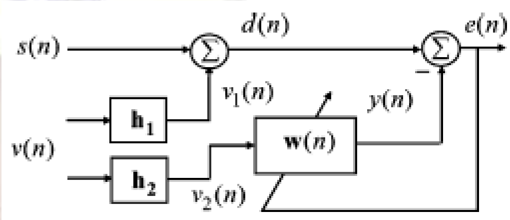

Fig. 1. Adaptive noise canceller.

Where μ is a step-size parameter, $e^{*}(n)$ denotes the complex conjugate of the error signal $e(n)$, and $x(n) = (x(n),\ldots,\ x(n-L+1))^{T}$ is the data vector containing L samples of the reference signal $V_2(n)$.

Many ANCs [1]–[4] have been proposed in the past years using modified LMS algorithms in order to simultaneously improve the tracking ability and speed of convergence. Bershad has studied the performance of the normalized LMS (NLMS) algorithm with an adaptive step size in showing advantages in convergence time and steady state. Later, Douglas and Meng [4] have proposed the optimum nonlinearity for any input probability density of the independent input data samples, obtaining the normalized data nonlinearity adaptation (NDN-LMS). Although the latter algorithm is designed to improve the steady state performance, its derivation did not consider the ANC in case of a strong target signal in the primary input. Greenberg's modified-LMS (M-LMS) [2] extended the latter approach to the case of the ANC with the nonlinearity applied to the data vector and the target signal itself, obtaining substantial improvements in the performance of the canceller. The disadvantage of this method is that it requires a priori information about the processes which is generally unknown. Recently, an interesting approach has been proposed based on a nonlinearity applied exclusively to the data vector [3].

This paper shows a novel adaptation for filtering speech signals in discontinuous speech transmission (DTX) systems, which are characterized by sudden changes of the signal statistics. The method is derived assuming stability in the sequence of a posteriori errors instead of the more restrictive hypothesis used in previous approaches i.e., enforcing it to vanish.

II. CS-LMS ALGORITHM

The NLMS algorithm may be viewed as the solution to a constrained optimization problem [6]. The problem of interest may be stated as follows: given the tap-input vector $x(n)$ and the desired response $d(n)$, determine the tap weight vector $\omega(n+1)$ so as to minimize the squared Euclidean norm of the change $\delta\omega(n+1) = \omega(n+1) - \omega(n)$ in the tap-weight vector $\omega(n+1)$ with respect to its old value $\omega(n)$, subject to the constraint $\omega(n+1)^H x(n) = d(n)$, where H denotes the Hermitian transpose. This constraint means that the a posteriori error sequence vanishes $[e^{[k+1]}(n) \equiv d(n) - w(k+1)^H x(n) = 0,\ \text{for}\ k = n]$.

In order to solve this optimization problem, the method of Lagrange multipliers is used with the Lagrangian function

$$L(\omega(n+1)) = \| \delta\omega(n+1) \|^2 + \mathrm{Re}[\lambda^* e^{(n+1)}(n)] \quad (2)$$

Where λ^* is the Lagrange multiplier, thus obtaining the well known adaptation rule in (1) with the normalized step size given by $\mu = \hat{\mu}\|x(n)\|^2$. The latter constraint is overly restrictive in real applications; thus, if we relax it, another interesting solution can be derived. Consider the constrained optimization problem that provides the following cost function:

$$L(w(n+1)) = \|\delta w(n+1)\|^2 + \mathrm{Re}[\lambda^* \delta e^{[n+1]}(n)] \quad (3)$$

Where $\delta e^{[n+1]}(n) \equiv e^{[n+1]}(n) - e^{[n+1]}(n-1)$. This equilibrium constraint ensures stability in the sequence of a posteriori errors, i.e., the optimal solution $w^{opt}(n+1)$ is the one that renders the sequence of errors as smooth as possible. Taking the partial derivative of (3) with respect to the vector $w^H(n+1)$ and setting it equal to zero leads to

$$\frac{\partial L(w(n+1))}{\partial w^H(n+1)} = \frac{\partial \delta w^H(n+1)\delta w(n+1)}{\delta w^{H(n+1)}} + \frac{\partial}{\delta w^{H(n+1)}} \times \mathrm{Re}[\lambda^* (e^{[n+1]}(n) - e^{[n+1]}(n-1))] \quad (4)$$

Since $e^{[n+1]}(k) = d(k) - w^H(n+1)x(k)$ for k=n,n-1 and $\mathrm{Re}[z] = 1/2(z + z^*)$, then

$$\frac{\delta L(w(n+1))}{\delta w^H(n+1)} = \delta w(n+1) - \frac{1}{2}\lambda^* \delta x(n) = 0 \quad (5)$$

Where $\delta x(n) = x(n) - x(n-1)$ is the difference between two consecutive input vectors. Hence, the step of the algorithm is

$$\delta w(n+1) = \frac{1}{2}\lambda^* \delta x(n) \Rightarrow w(n+1) = w(n) + \frac{1}{2}\lambda^* \delta x(n). \quad (6)$$

Finally, after multiplying both sides of (5) by $\delta x^H(n)$, the Lagrange multiplier can be expressed as

$$\lambda^* = \frac{2\delta x^H(n)\delta w(n+1)}{\|\delta x(n)\|^2} = -\frac{2(\delta e^{[n+1]}(n) - \delta e^{[n]}(n))^*}{\|\delta x(n)\|^2} \quad (7)$$

where $\delta e^{[n]}(n) = e^{[n]}(n) - e^{[n]}(n-1)$ is the difference in the a priori error sequence [denoted by $\delta e(n)$ for short], since the numerator on the left-hand side of (7) is equal to $x^H(n)w(n+1) - x^H(n-1)w(n+1) - x^H(n)w(n) + x^H(n-1)w(n)$. Therefore, applying the equilibrium constraint on the right-hand side of (7) $(\delta e^{(n+1)}(n) = 0)$ leads to

$$\lambda = \frac{2\delta\, e^{[n]}(n)}{\|\delta x(n)\|^2} \quad (8)$$

Finally, the minimum of the Lagrangian function satisfies the following constrained stability update condition (CS-LMS)

$$\omega(n+1) = \omega(n) + \frac{\delta\, x(n)\delta e^*(n)}{\|\delta x(n)\|^2} \quad (9)$$

The weight adaptation rule can be made more robust by introducing a small positive constant ε into the denominator to prevent numerical instabilities in case of a vanishingly small squared norm $\|\delta x(n)\|^2$ and by multiplying the weight increment by a constant step size μ to control the speed of the adaptation. Note that the equilibrium condition enforces the convergence of the algorithm if $\|\delta x(n)\|^2 \neq 0$. Several learning algorithms, where the learning relies on the concurrent change of processing variables, have been proposed in the past for decorrelation, blind source separation, or deconvolution applications [5]. Stochastic information gradient (SIG) algorithms [5] maximize (or minimize) the Shannon's entropy of the sequence of errors using an estimator based on an instantaneous value of the probability density function (pdf) and Parzen windowing. In this way, the CS-LMS algorithm can be considered as a generalization of the single sample-based SIG algorithm using variable kernel density estimators.

III. THEORETICAL REMARKS ON THE CS-LMS ADAPTATION

Once the CS-LMS method has been derived, a comparison is established with the NLMS algorithm. This section shows that, under some conditions: 1) CS-LMS and NLMS algorithms converge to the optimal Wiener solution ω_0 , and 2) for any fixed step size μ, the proposed CS-LMS exhibits improvements in excess minimum squared error (EMSE) and misadjustment (M) [6] when compared to the NLMS algorithm.

A. Convergence Analysis of CS-LMS

Theorem 1 (Convergence Equivalence): Let $x(n)$ be the tap inputs to a transversal filter and $\omega(n)$ the corresponding tap weights. The estimation error $e(n)$ is obtained by comparing the estimate $y(n)$ provided by the filter with the desired response $d(n)$, that is $e(n) = d(n) - y(n)$. On the other hand, if the desired signal $d(n)$ is generated by the multiple linear regression model, i.e., $d(n) = w_o^H x(n) + e_o(n)$, where $e_o(n)$ is an uncorrelated white-noise process that is statistically independent of the input vector $x(n)$, then the CS-LMS adaptation converges to the Wiener solution $w_o(n)$ under stationary environment.

Proof: This theorem is proven by showing that $w_o^{'} = \arg\min_w E[|\delta e(n)|^2$ is equal to $\arg\min_w E[|\delta e(n)|^2 = w_0$.. This condition is satisfied since the cross-correlation vector between the concurrent change in the desired responses (δd) and input-vectors $(\delta\, x), r_{\delta d\delta x} \equiv E[\delta x \delta d^*] = R_{\delta x}\omega_0$, where $R_{\delta x} \equiv E[\delta x \delta x^H]$ denotes auto-correlation matrix of $\delta\, x$.

B. Learning Curves of the CS-LMS Algorithm: EMSE and Misadjustment

It is common in practice to use ensemble-average learning curves to study the statistical performance of adaptive filters. The derivation of these curves is slightly different for the ANC problem due to the presence of the desired clean signal $s(n)$. Using the definition of the weight-error vector $\varepsilon(n) = w_0 - w(n)$ and (9) with the step size defined as μ, we may express the evolution of $\varepsilon(n)$ as

$$\varepsilon(n+1) = \varepsilon(n) - \mu\delta x(n) \quad X(\delta\, s(n) + \delta v(n) - (w_0 - \varepsilon(n))^H \delta\, x(n)^* \tag{10}$$

Where $\delta[.](n) = [.](n) - [.](n-1)$ and $v(n)$ denotes the noise in the primary signal $d(n)$ (V_1 in Fig .1). If $v(n)$ is assumed to be generated by the multiple regression model: $v(n) = \omega_0^H x(n) + e_0(n)$, the weight-error vector is expressed as

$$\varepsilon(n+1) = (I - \mu\delta x(n)\delta x(n)^H \varepsilon(n) - \mu\delta x(n)(\delta e_0(n) + \delta s(n))^*. \tag{11}$$

By invoking the direct-averaging method [6], the equation above leads to

$$\varepsilon_0(n+1) = (I - \mu\, R_{\delta x})\varepsilon_0(n) - \mu\delta x(n)\delta\, e_0^*(n) \tag{12}$$

Where $\delta e_0(n) = \delta e_0(n) + \delta s(n)$, and the mean-squared error produced by the filter is given by

$$J(n) = J_0 + E\left[|\, s(n)\,|^2\right] + E\left[\varepsilon_0^H(n) x(n) x(n)^H \varepsilon_0(n)\right] \tag{13}$$

Where $J_0 = E\left[|\, e_0(n)\,|^2\right]$ and $J_{min} = J_0 + E\left[|\, s(n)\,|^2\right]$. The stochastic evolution on the natural modes can be studied by transforming (12) into

$$v(n+1) = (I - \mu\wedge)v(n) - \phi(n) \tag{14}$$

and by applying the unitary similarity transformation [6] to the correlation matrix $R_{\delta x}$, where $\wedge = Q^H R_{\delta x} Q$ is a diagonal- matrix consisting of the eigenvalues λ_k of $R_{\delta x}$,Q, is a unitary matrix whose columns constitute an orthogonal set of eigenvectors and the stochastic force vector is defined as $\phi(n) = \mu Q^H \delta x(n) \delta e_0^*(n)$. This vector has the following properties.

- The mean of the stochastic force vector $\phi(n)$ is zero: $E[\phi(n)] = 0$.
- The correlation matrix of the stochastic force vector is a diagonal matrix: $E[\phi(n)\phi^H(n)] = \mu^2 J \wedge$, where $J = 2(E[|\, e_0(n)^2\,|] + E[|\, s(n)^2\,|] - \mathrm{Re}\{r_s(1)\})$, and $r_s(1) \equiv E[s^*(n+1)s(n)]$.

The first two moments of the natural modes can be obtained by using these properties as in [6], which allow one to show the evolution of $J(n)$ with time step n . The third term of (13), in light of the direct-averaging method, is equal to

$$J_{ex}(n) = E[\varepsilon_0^H(n) x(n) x(n)^H \varepsilon_0(n)]$$

$$\approx E[\varepsilon_0^H(n) R \varepsilon_0(n)] = \mathrm{tr}\{RE[\varepsilon_0(n)\varepsilon_0^H(n)]\}$$

$$= \frac{1}{2}\sum_{k=1}^{L} \lambda_k E[|\, v_k(n)\,|^2] + E[rt\{v^H Q^H\, \mathrm{Re}\{R(1)\} Qv\}] \tag{15}$$

where $R(1)=E[x(n+1)x^{H}(n)]$. Assuming that the input signal is weakly correlated $(R(1)\sim 0)$, the second term can be bounded in the last equality of (15) with the first term (natural evolution), i.e., $E[tr\{v^{H}Q^{H}\ Re\{R(1)\}Qv\}]\leq (1/2)\sum_{k=1}^{L}\lambda_{k}E[|v_{k}(n)|^{2}]$, and then

$$J_{ex}(n)\leq\sum_{k=1}^{L}\lambda_{k}E[|v_{k}(n)|^{2}]$$

$$=\sum_{k=1}^{L}\lambda_{k}\left(\frac{\mu J}{2-\mu\lambda_{k}}+(1-\mu\lambda_{k})^{2n}\right.$$

$$\left.X\left(|v_{k}(0)|^{2}-\frac{\mu J}{2-\mu\lambda_{k}}\right)\right) \quad (16)$$

where $v_k(n)$ denotes the k th-component of natural mode $v(n)$ [6]. If the exponential factor is neglected with increasing n

$$J_{ex}(\infty)\leq\sum_{k=1}^{L}\lambda_{k}\left(\frac{\mu J}{2-\mu\lambda_{k}}\right)\approx\frac{1}{2}\mu\ J\ tr\{R_{\delta x}\} \quad (17)$$

the reduction in $J_{ex}(\infty)$ is achieved whenever

$$J_{ex}(\infty)\approx\frac{1}{2}\mu\ J\ tr\{R_{\delta x}\}\approx\mu\ J\ tr\{R\}$$

$$\leq J_{ex}^{LMS}(\infty)\approx\frac{1}{2}\mu\ J_{min}tr\{R\}\Leftrightarrow Re\{r_{s}(1)\}$$

$$\geq\frac{3}{4}J_{min} \quad (18)$$

i.e., the desired signal is strongly correlated. It also follows from classical analysis [6] that 1) the high value of μ balances the trade-off between $J_{ex}(\infty)$ and the average time constant T since

$$T\approx\frac{L}{\mu\ tr\{R_{\delta x}\}} \quad (19)$$

Where L is the filter length, and 2) a necessary condition for stability is that $0<\mu<2/\lambda_{k}$, for all k.

IV simulation setup

The desired speech and noise statistical parameters as follows:

Desired speech:

Frequency: 4000Hz,
Sampling Frequency: 8000Hz

Noise Parameters:

Amplitude: 0.15
Type: normal distribution noise:
Mean: 0
Variance: 1.01
Initial Seed: 10

Filter Specifications used:

Filter Type: FIR
Order: 32
Structure: Direct form-I
Window: Rectangular
No. Of Iterations: 100 to 1000

V Results

The signals above described in simulation setup are taken as the input to the adaptive filter and the filter coefficients are updated using the constrained stability LMS algorithm and standard LMS algorithm. We compare the performance characteristics of both algorithms finally.

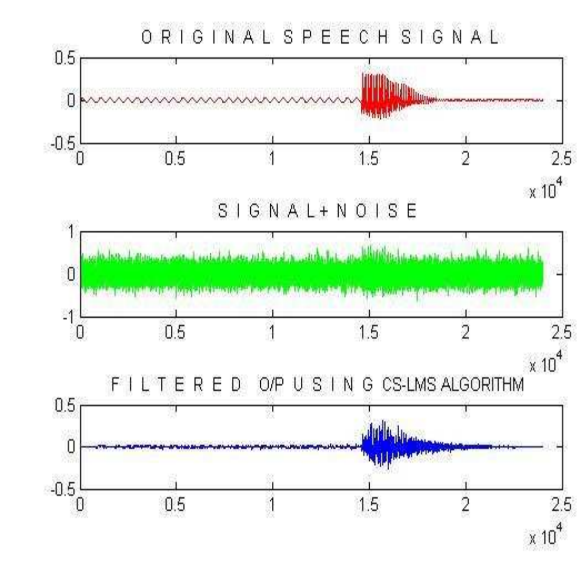

Fig 1: simulated result of noise cancellation In speech using CS-LMS algorithm

No. of iterations	CS- LMS algorithm	LMS1 (μ1=0.05)	TV LMS μ=0.02
100	0.0367	0.0428	0.0326
200	0.0183	0.0213	0.0176
300	0.0121	0.0142	0.0126
400	0.0091	0.0106	0.0100
500	0.0073	0.0085	0.0084
600	0.0061	0.0071	0.0073
700	0.0052	0.0061	0.0064
800	0.0045	0.0053	0.0058
900	0.0040	0.0047	0.0053
1000	0.0036	0.0042	0.0049

Table 1: Indicates MSE Comparison after Performing various no of Iterations in Standard LMS, CS-LMS, TV –LMS

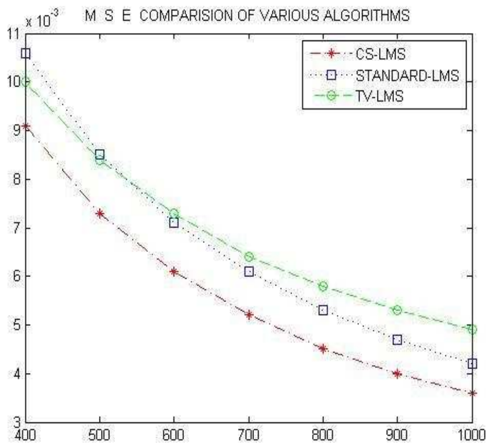

Fig 2: Learning curve of various algorithms
For noise cancellation in same speech signal

VI CONCLUSION AND FUTURE SCOPE

This paper presented a novel CS-LMS algorithm based on the concept of difference quantities and the constraint of equilibrium condition in the sequence of a posteriori estimation errors. The method, which applies nonlinearities to the error and input signal sequences, is derived using the Lagrange multiplier method as a generalization of the LMS algorithm. Under certain conditions, the proposed ANC based on the CS-LMS algorithm showed improved performance by decreasing the Mean-Squared Error compared to the standard LMS and Time Varying LMS algorithms. As shown in the figure 2. we can conclude that CS-LMS algorithm is producing optimized response, while producing very small MSE's compared with standard LMS and time varying LMS algorithms.

We can efficiently use this CS-LMS algorithm in Sub-Band Adaptive filtering Applications in order to produce optimized response. So undoubtedly this algorithm has appreciable significance in speech processing.

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