A NOVEL APPROACH TO DESIGN AN ADAPTIVE FILTER FOR AN ACOUSTIC ECHO CANCELLATION APPLICATION

Ashok R*1
Amjad khan G*2

*1 M.Tech student, G Pulla Reddy Engineering College, Kurnool

*2 Assistant Professor, M.Tech, (Ph.D), G Pulla Reddy Engineering College, Kurnool

ABSTRACT

In general an adaptive filter performs more efficient than normal filters, but suffers with ill-posed problem. This problem is due to noise in the observation data or solving linear system of equations. By using regularization concept we optimize this problem. In this paper we proposed a regularization parameter for four important adaptive algorithms: the normalized least-mean-square (NLMS), the signed-regressor NLMS (SR-NLMS), the improved proportionate NLMS (IPNLMS), and the SR-IPNLMS. Simulations performed on an AEC application, which is basically a system identification problem, with different ENRs.

Index Terms: Echo to Noise Ratio (ENR), improved proportionate NLMS (IPNLMS), normalized least-mean square (NLMS), regularization, signed-regressor NLMS (SR-NLMS), SR-IPNLMS.

I. INTRODUCTION

An adaptive filter is a dynamic filter, which self-adjusts its transfer function according to an optimization algorithm driven by an error signal. In adaptive filtering, we always have a linear system of equations, which are over determined or underdetermined. We face an ill-posed problem to solve these equations and also when the observation data is noisy, which is common in all applications. By using regularization concept we optimize this problem and this is done by adding additional information to the existing system. As a result, regularization is an important design part in any adaptive filter to behave properly.

The regularization parameter (δ) is taken as

$$\delta = \beta\, \sigma_x^2 \qquad (1)$$

Where $\sigma_x^2 = E[x^2(n)]$ is the variance of the zero-mean input x(n),where E[.] denoting mathematical expectation, and β is a positive constant. In practice β is more a variable that depends on the level of the additive noise. The more the noise, the larger is the value of β. we will also refer β as the normalized regularization parameter.

The basic block diagram of adaptive filter is shown in figure (1), which contains 3 basic sections.

1. Filtering Section

2. Adaptive Section

3. Error Section

Here the input signal x(n) is given as input to filtering section, which changes its filter coefficients according to the feed back from adaptive section. In adaptive section we use an adaptive algorithm (LMS, NLMS, RLS…etc) to update the filter coefficients. The error section is used to calculate the error between estimated filter output y(n) and desired output d(n).

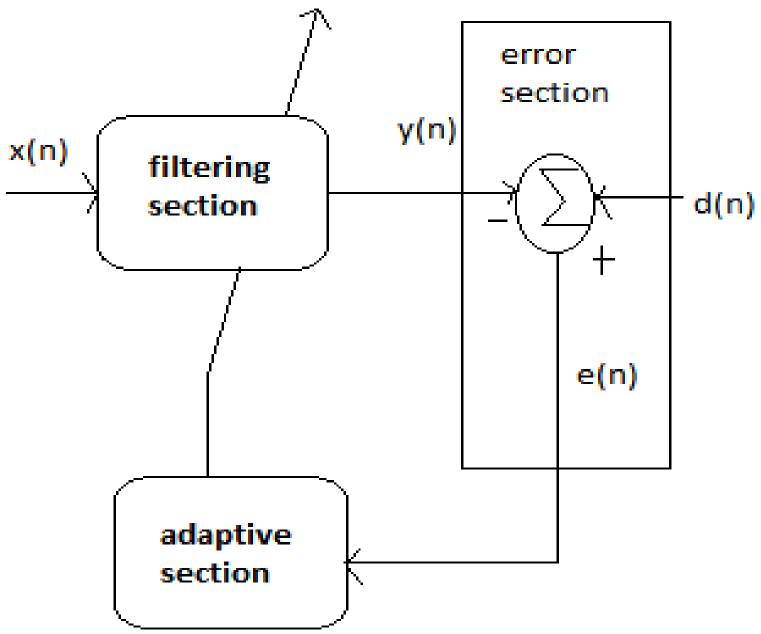

Fig 1: Basic block diagram of an adaptive filter

The following equations (2 to 4) are basic equations of an adaptive filter,i.e.

Filter output $$y[n] = \sum_{k=0}^{M-1} x[n-k] w_k^*[n] \tag{2}$$

Error signal $$e(n) = d(n) - y(n) \tag{3}$$

Updated tap weight vector $$w(n+1) = w(n) + \mu e(n) x(n) \tag{4}$$

The importance regularization is measured with parameter misalignment, which is a distance measure between the true impulse response and the estimated one with an adaptive algorithm. The misalignment decreases smoothly with time and converges to a stable and small value by using regularization. Without this regularization parameter δ, the misalignment of the adaptive filter may fluctuate and may never converge.

II. REGULARIZATION OF THE NLMS ALGORITHM

The NLMS algorithm is summarized by the following two expressions:

$$e(n) = d(n) - x^T(n)\,\hat{w}(n)$$

$$= d(n) - y(n) \qquad (5)$$

$$\hat{w}(n+1) = \hat{w}(n) + \alpha \frac{e(n)x(n)}{\delta + x^T(n)x(n)} \qquad (6)$$

where α (0< α<2) is the normalized step-size parameter and δ is the regularization parameter of the NLMS.

To find the value of regularization parameter δ the following assumptions are made.

Since $e(n) = d(n) - x^T(n)\hat{w}(n)$ is the error signal between the desired signal and the estimated signal. We should find δ in such a way that the expected value of $e^2(n)$ is equal to the variance of the noise, i.e.,

$$E[e^2(n)]=\sigma^2_{w}. \qquad (7)$$

This is reasonable if we want to attenuate the effects of the noise in the estimator w (n).

To derive the optimal according to (4), we assume in the rest that L>>1 and x (n) is stationary, As a result,

$$x^T(n)x(n) \approx L\sigma^2_X \qquad (8)$$

Developing (7) and using (8), we easily derive the quadratic equation

$$\delta^2 - 2\frac{L\sigma_x^2}{ENR} - \frac{(L\sigma_x^2)^2}{ENR} = 0 \qquad (9)$$

from which we deduce the obvious solution

$$\delta = \frac{L(1+\sqrt{1+ENR})}{ENR}\sigma_x^2$$

$$= \beta_{NLMS}\sigma_x^2 \qquad (10)$$

where

$$\beta_{NLMS} = \frac{L(1+\sqrt{1+ENR})}{ENR} \qquad (11)$$

is the normalized regularization parameter of the NLMS.

From the above equation we observed that δ depends on three elements: the length of the adaptive filter (L), the variance of the input signal (σ^2_x) and the ENR. In an acoustic echo cancellation, the first two elements (L and σ^2_x) are known, while the ENR is often roughly known or can be estimated.

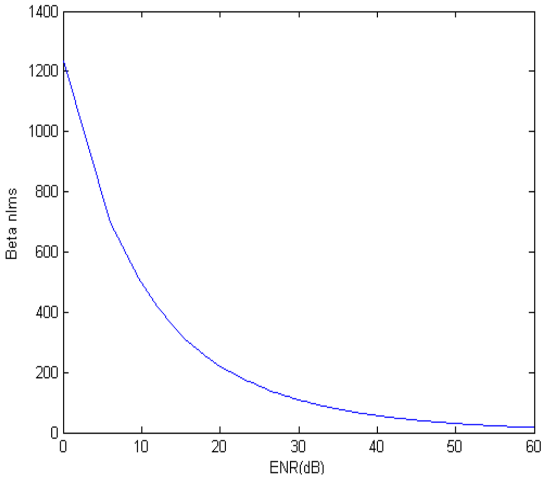

Fig.2.Normalized regularization parameter β_{NLMS} as a function of the ENR with L=512.The ENR varies from 0 to 50 dB.

III. REGULARIZATION OF THE SR-NLMS ALGORITHM

The equations of the SR-NLMS algorithm are

$$e(n) = d(n) - y(n) \qquad (12)$$

$$\hat{w}(n+1) = \hat{w}(n) + \alpha \frac{e(n)\mathrm{sgn}(x(n))}{\delta + x^T(n)\mathrm{sgn}(x(n))} \qquad (13)$$

Where sgn [x (n)] is the sign of each component of x(n) and δ is the regularization parameter of the SR-NLMS. This algorithm is very interesting from a practical point of view because its performance is equivalent to the NLMS but requires less multiplication at each iteration time as noticed in (13).

For L>>1and a stationary signal x(n), we have

$$\delta = \frac{L\beta_x (1+\sqrt{1+ENR})}{ENR}\sigma_x^2$$
$$=\beta_{SR-NLMS}\sigma_x^2 \qquad (14)$$

Where

$$\beta_{SR-NLMS} = \frac{L\beta_x (1+\sqrt{1+ENR})}{ENR} \qquad (15)$$

is the normalized regularization parameter of the SR-NLMS.

IV. REGULARIZATION OF THE IPNLMS ALGORITHM

When the target impulse response is sparse, it is possible to take advantage of this sparsity to improve the performance of the classical adaptive filters. In PNLMS algorithm each coefficient of the filter is independent of the others by adjusting the adaptation step size in proportion to the magnitude of the estimated filter coefficient. It redistributes the adaptation gains among all coefficients and emphasizes the large ones (in magnitude) in order to speed up their convergence and, consequently, achieving a fast initial convergence rate. The IPNLMS is an improved version of the PNLMS and works very well even if the impulse response is not sparse, which not the case is for the PNLMS. The IPNLMS expressions are

$$e(n) = d(n) - y(n) \tag{16}$$

$$\hat{w}(n+1) = \hat{w}(n) + \alpha \frac{G(n-1)e(n)x(n)}{\delta + x^T(n)G(n-1)x(n)} \tag{17}$$

Where δ is the regularization parameter of the IPNLMS, $G(n-1) = \mathrm{Diag}[g_0(n-1)\ g_1(n-1).....g_{L-1}(n-1)]$ is an $L \times L$ diagonal matrix.

For L>>1and a stationary signal x(n), we have

$$\delta = \frac{(1+\sqrt{1+ENR})}{ENR}\sigma_x^2$$

$$= \beta_{IPNLMS}\sigma_x^2 \tag{18}$$

Where

$$\beta_{IPNLMS} = \frac{(1+\sqrt{1+ENR})}{ENR} \tag{19}$$

is the normalized regularization parameter of the IPNLMS.

V. REGULARIZATION OF THE SR-IPNLMS ALGORITHM

The extension of the SR principle to the IPNLMS is observed in SR-IPNLMS algorithm. Therefore, the SR-IPNLMS is summarized by the following two equations:

$$e(n) = d(n) - y(n) \tag{20}$$

$$\hat{w}(n+1) = \hat{w}(n) + \alpha \frac{G(n-1)e(n)\,\mathrm{sgn}\,(x(n))}{\delta + x^T(n)G(n-1)\,\mathrm{sgn}\,(x(n))} \tag{21}$$

Where is the regularization parameter of the SRIPNLMS and G (n-1) is defined in the previous section.

For L>>1and a stationary signal x(n), we have

$$\delta = \frac{\beta_X(1+\sqrt{1+ENR})}{ENR}\sigma_X^2$$

$$= \beta_{SR-IPNLMS}\sigma_X^2 \qquad (22)$$

Where

$$\beta_{SR-IPNLMS} = \frac{\beta_X(1+\sqrt{1+ENR})}{ENR} \qquad (23)$$

is the normalized regularization parameter of the SR-IPNLMS.

VI. SIMULATIONS

The measured acoustic impulse response used in simulations is depicted in Fig. 3. It has 512 coefficients and the same length is used for the adaptive filter (i.e. L=512); the sampling rate is 8 kHz. The input signal x(n) is either a whit Gaussian noise or a speech sequence. An independent white Gaussian noise is added to the echo signal with different values of the ENR.

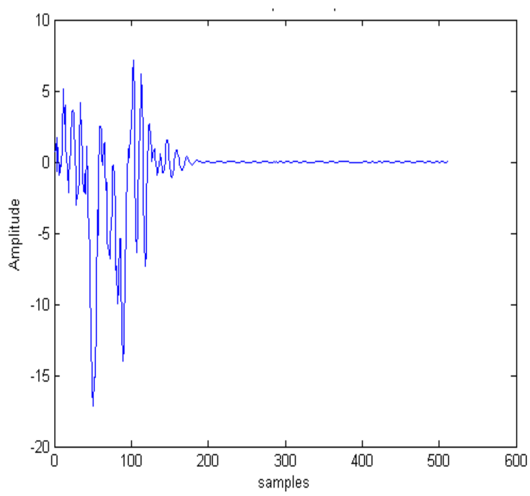

Fig.3.Acoustic impulse response used in simulations.

The performance is evaluated in terms of the normalized misalignment (in dB), defined as

$$20\log_{10}\frac{\|\hat{w}(n)-w\|_2}{\|w\|_2} \qquad (24)$$

Where $\hat{w}(n)$ is estimate of tap weight vector w.

In the first set of experiments, the performance of the NLMS algorithm is evaluated. Fig. 4 presents the misalignment of this algorithm using different values of the normalized regularization constant β [see (1)], as compared to the "optimal" normalized regularization given β_{NLMS} in (11). The ENR is set to 30 dB and the input signal is white and Gaussian. According to this figure, it is clear that a lower misalignment level is achieved for a higher normalized regularization constant, but with a slower convergence rate and tracking.

The same experiment is repeated in Fig. 5, but using a lower value of the ENR, i.e., 0dB. It is clear that the importance of the "optimal" regularization becomes more apparent. In order to match the performance obtained with β_{NLMS} the normalized regularization constant needs to be further increased(i.e., β=1200).All these results are in consistence with Fig. 1, which provides the values of β_{NLMS} as a function of the ENR.

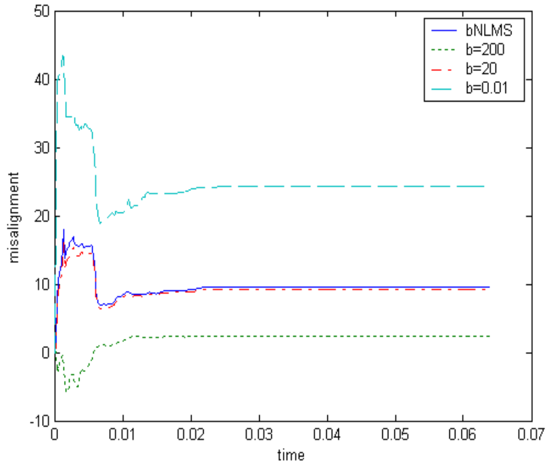

Fig.4. Misalignment of the NLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, L=512, and ENR=30dB.

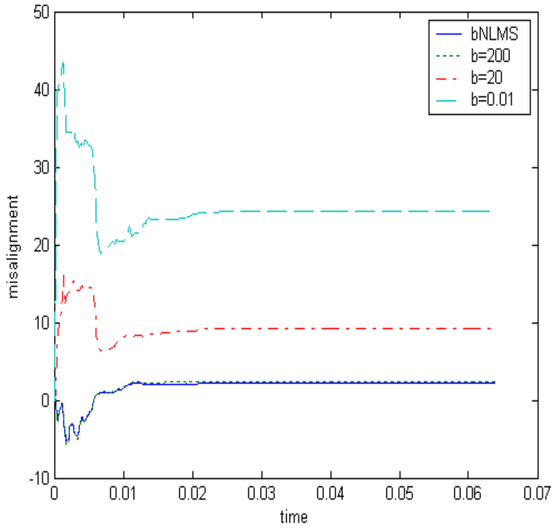

Fig.5. Misalignment of the NLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, L=512, and ENR=0dB.

Commonly, the SR-NLMS algorithm uses a similar regularization to the NLMS algorithm i.e., $\beta_{SR\text{-}NLMS}=\beta_x\ \beta_{NLMS}$. Fig.6 presents the misalignment of the SR-NLMS algorithm with different values of β from (1), as compared to the "optimal" normalized regularization $\beta_{SR\text{-}NLMS}$ given in(12).The input signal is white and Gaussian, and ENR=10dB. The SR-NLMS algorithm with (which is close to the value β=170) performs much better in terms of both fast convergence/tracking and misalignment. However, for lower values of the ENR, the normalized regularization constant needs to be further increased. The experiment reported in

Fig. 7 is performed with ENR=0dB. Again, the SR-NLMS algorithm with $\beta_{SR\text{-}NLMS}$ (which is now close to the value β=1000) gives the best performance.

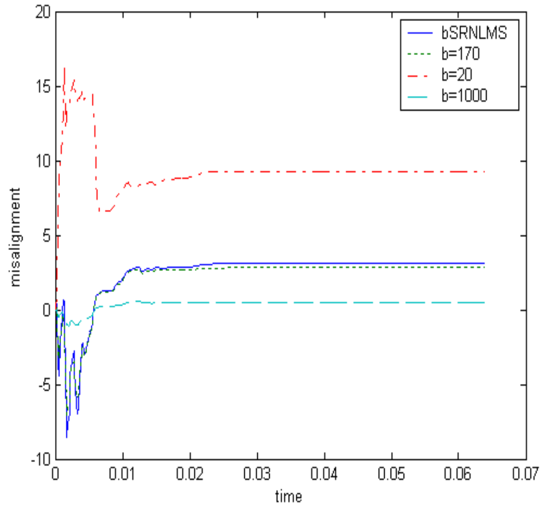

Fig.6. Misalignment of the SR-NLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, L=512, and ENR=10dB.

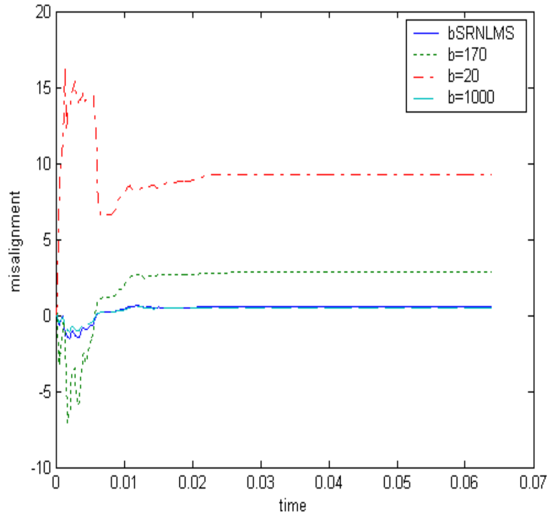

Fig.7. Misalignment of the SR-NLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, L=512, and ENR=0dB.

The IPNLMS algorithm is very useful when we need to identify sparse impulse responses, which is often the case in network and acoustic echo cancellation. The regularization parameter of this algorithm should be taken as $\delta_{IPNLMS}=\delta_{NLMS}(1-k)/(2L)$. However, as it was proved in Section IV, the regularization of the IPNLMS algorithm does not depend on the parameter k (that controls the amount of proportionality in the algorithm).

The "optimal" regularization of the IPNLMS algorithm is equivalent to the regularization of the NLMS up to the scaling factor L, i.e, $\beta_{IPNLMS}=\beta_{NLMS}/L$.

The next set of experiments evaluates the performance of the IPNLMS algorithm. The proportionality parameter is set to k=0. The misalignment of this algorithm using the "classical" normalized regularization constant β=20/2L, as compared to the "optimal" normalized regularization β_{IPNLMS}. The input signal is white and Gaussian, and ENR=10dB. In this case, a much higher value of the normalized regularization constant is required [i.e., β=400/ (2L)], in order to match the performance obtained using β_{IPNLMS}.

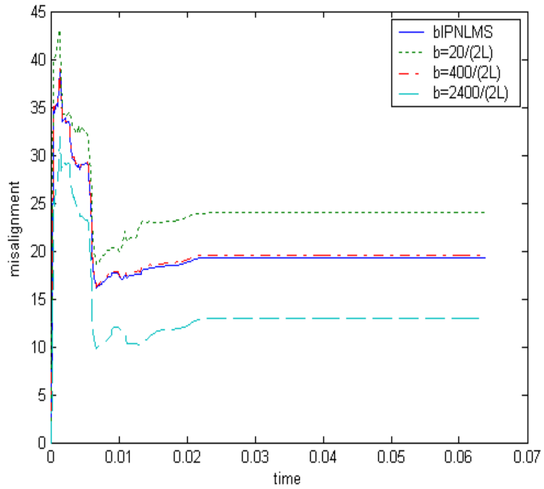

Fig.8. Misalignment of the IPNLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, k=0, L=512, and ENR=10dB.

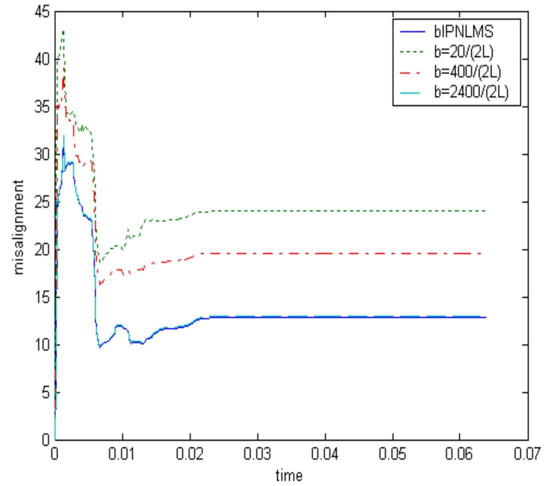

Fig.9. Misalignment of the IPNLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, k=0, L=512, and ENR=0dB.

This is also supported in Fig. 9, where ENR=0dB, so that the normalized regularization constant needs to be further increased [up to β=2400/ (2L)] in order that the IPNLMS performs in a similar way when the "optimal" choice is used.

Finally, the performance of the SR-IPNLMS algorithm is evaluated. The relation between the regularization parameters of the SR-IPNLMS and IPNLMS algorithms is, i.e., $\beta_{SR\text{-}IPNLMS}= \beta_x \beta_{IPNLM.}$ In Fig.10, the input signal is white and Gaussian, and ENR=10dB.

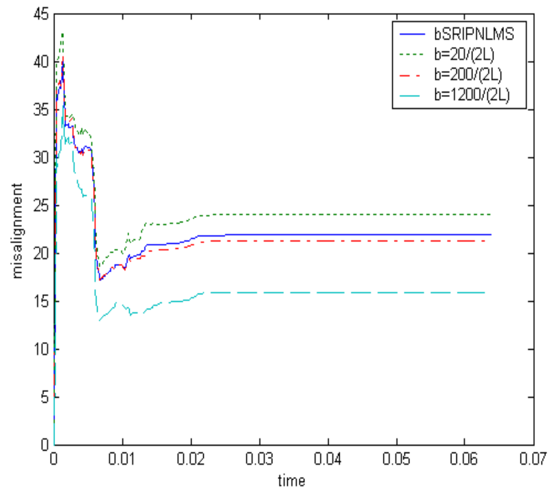

Fig.10. Misalignment of the SR-IPNLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, k=0, L=512, and ENR=10dB.

According to this figure ,it is clear that the SR-IPNLMS algorithm using the "optimal" value $\beta_{SR\text{-}IPNLMS}$ performs better as compared to the regular normalized regularization β=20/(2L). Also, it can be noticed that a lower misalignment level can be obtained by using a higher normalized regularization parameter, i.e., β=200/(2L).

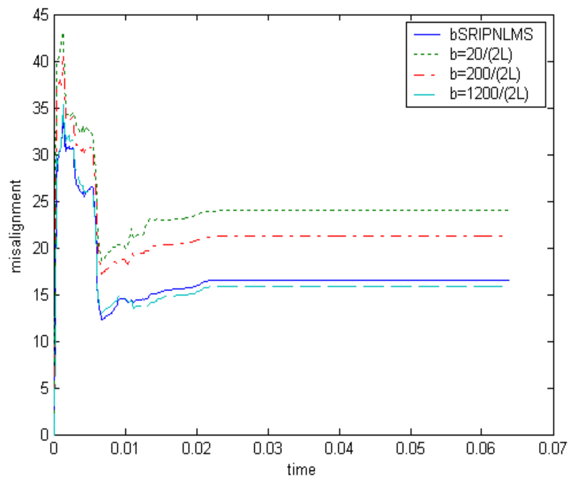

Fig.11. Misalignment of the SR-IPNLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, k=0, L=512, and ENR=0dB.

In Fig.11 we consider ENR=0dB and it is clear that a higher normalized regularization parameter is required now [i.e., β=1200/(2L)] to match the performance obtained with β of SR-IPNLMS.

VII. CONCLUSION

In this paper, we have proposed a simple condition, for the derivation of an optimal regularization parameter. From this condition we have derived the optimal regularization parameters of four algorithms: the NLMS, the SR-NLMS, the IPNLMS, and the SR-IPNLMS.

Extensive simulations have shown that with the proposed regularization, the adaptive algorithms behave extremely well at all ENR levels and this design is used for an acoustic echo cancelation application.

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Author Biographies

Mr. G.Amjad Khan obtained his M.Tech in Communication and Signal Processing from Sri Krishna Devaraya University in 2006. He is currently pursuing Ph.D degree from Rayalaseema University, Kurnool, India. He presented papers more than 7 in National conferences and 1 International conference and published 4 papers in International journals. He is presently working as Assistant Professor in ECE Department, G. Pulla Reddy Engineering College, Kurnool, A.P, India. His research interests include Adaptive signal Processing, Digital Signal Processing.

Mr. **R.ASHOK** is pursuing his M.Tech in Communication and Signal Processing (C.S.P) at G.Pulla Reddy Engineering College, Kurnool, A.P, India. He presented 2 papers in National conference. His area of interest is in the field of Digital Signal Processing.