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Performance Analysis of Regularized Adaptive Filter for an Acoustic Echo Cancellation Application

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Abstract: ***Currently, adaptive echo cancellation algorithm is mainstream technology in the field of noise cancellation. In general an adaptive filter performs more efficient than normal filters, but suffers with ill-posed problem. This problem is due to echo 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). Simulations performed on an ANC application, which is basically a system identification problem, with different ENRs.***

Keywords: Echo to Noise Ratio (ENR),normalized least-mean square (NLMS), regularization

1. Introduction

With the development of telecommunications technology in China, people pay more attention to voice quality. In recent years, in order to improve voice quality, dual microphone noise canceling system is widely used in hearing aids, video conferencing, handheld communication devices and etc. Noise cancellation algorithms include beam forming, the first-order differential sensor and ANC, wherein the ANC algorithm is mainstream technology in the field of eliminating noise, and the idea of ANC was first proposed in the 1970s by the B.Widrow, it developed rapidly in the last 40 years. The ANC system can adapt to the statistical characteristics of the signal and noise change by continuously adjusting the tap coefficient weights in unknown circumstances.

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 echo. The more the echo, the larger is the value of β. we will also refer β as the normalized regularization parameter.

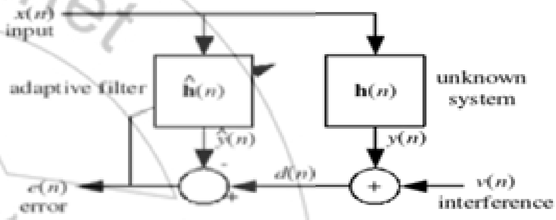

Figure 1: Adaptive Filter

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

Here the input signal x (n) is given as input to filtering section, which changes its filter coefficients according to the feedback 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).+The following equations (2 to 4) are basic equations of an adaptive filter,i.e.

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

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

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

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.

2. Regularization of the NLMS Algorithm

The NLMS algorithm is summarized by the following two expressions:

$$e(n) = d(n) - x^T(n)\hat{w}(n)$$
$$= d(n) - \tilde{y}(n) \qquad (5)$$

$$h(n) = h(n-1) + \alpha \frac{e(n)x(n)}{\delta + x^T(n)x(n)} \quad (6)$$

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

The question now is how to find δ?

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

Variance of the echo. i.e.

$$E[e^2(n)] = \sigma_w^2 \quad (7)$$

This is reasonable if we want to attenuate the effects of the echo 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

$$x^T(n)\, x(n) \approx L\sigma_X^2 \quad (8)$$

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

$$\delta^2 - 2\frac{L\sigma_X^2}{SNR} - \frac{\left((L\sigma_X^2)^2\right)}{SNR} = 0 \quad (9)$$

from which we deduce the obvious solution

$$\delta = \frac{L(1+\sqrt{1+ENR})}{ENR}\sigma_X^2 \quad (10)$$

$$= \beta_{NLMS}\sigma_X^2$$

Where

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

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 echo cancellation, the first two elements (L and σ^2_x) are known, while the ENR is often roughly known or can be estimated.

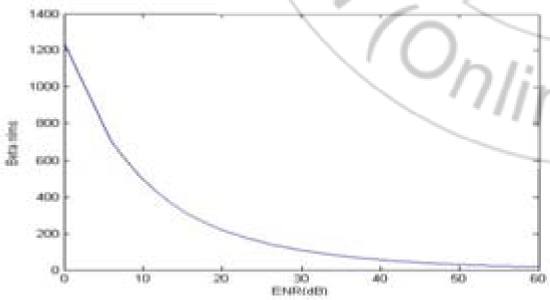

Figure 2: Normalized regularization parameter β_{NLMS} as a function of the ENR with L=512.The ENR varies from 0 to 60 dB.

3. Regularization of SR- NLMS Algorithm

The equations of the SR-NLMS algorithm are

$$e(n) = d(n) - \tilde{y}(n) \quad (11)$$

$$h(n) = h(n-1) + \alpha \frac{e(n)sgn(x(n))}{\delta + x^T(n)x(n)} \quad (12)$$

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 (4.30).

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

$$\delta = \frac{L\beta_x(1+\sqrt{1+ENR})}{ENR}\sigma_x^2$$
$$= \beta_{SR-NLMS}\sigma_X^2 \quad (13)$$

Where

$$\boldsymbol{\beta_{SR-NLMS}} = \frac{\boldsymbol{L\beta_x(1+\sqrt{1+ENR})}}{\boldsymbol{ENR}} \quad (14)$$

is the normalized regularization parameter of the SR-NLMS.

4. Regularization of IP- NLMS 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

$$e(n) = d(n) - \tilde{y}(n) \quad (15)$$

$$h(n) = h(n-1) + \alpha \frac{G(n-1)e(n)x(n)}{\delta + x^T(n)G(n-1)x(n)} \quad (16)$$

Where δis the regularization parameter of the IPNLMS,

$$G(n-1) = Diag[g_0(n-1), g_1(n-1) \ldots\ldots\ldots g_{L-1}(n-1) \quad (17)$$

is an L × L diagonal matrix.

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

$$\delta = \frac{(1+\sqrt{1+ENR})}{ENR}\sigma_x^2$$
$$= \beta_{IP-NLMS}\sigma_x^2 \quad (18)$$

$$\beta_{IP-NLMS} = \frac{(1+\sqrt{1+ENR})}{ENR} \quad (19)$$

is the normalized regularization parameter of the IPNLMS.

5. Regularization of SRIPNLMS 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:

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

$$\boldsymbol{h(n)} = h(n-1) + \boldsymbol{\alpha} \frac{\boldsymbol{G(n-1)e(n)sgn(x(n))}}{\boldsymbol{\delta + x^T(n)G(n-1)sgn(x(n))}} \quad (21)$$

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

$$\delta = \frac{\beta_x(1+\sqrt{1+ENR})}{ENR}\sigma_x^2$$
$$= \beta_{SR-IPNLMS}\sigma_x^2 \quad (22)$$

Where

$$\boldsymbol{\beta_{SR-IPNLMS}} = \frac{\boldsymbol{\beta_x(1+\sqrt{1+ENR})}}{\boldsymbol{ENR}} \quad (23)$$

is the normalized regularization parameter of the SR-IPNLMS.

6. Simulation Parameters

The input noisy signal and the desired signal and the filter parameters are same for all the four simulation procedures and they are characterized as follows,

Input signal parameters:
Amplitude: 1 V
Frequency: 4000Hz, 8000Hz
Sampling Frequency: 22500Hz
Initial Phase: 0
Noise Parameters:
Amplitude: 0.15 V
Noise frequency: 1500 Hz
Type: Gaussian
Mean: 0
Variance: 1
Initial Seed: 10
Filter Parameters
Filter Type: FIR
Order: 24, 40
Window: Rectangular
No. Of Iterations: 8000-72000
Convergence Factor: time varying
Desired signal parameters:
Frequency: 4000Hz
Amplitude: 1

7. Analysis of Simulation Results

Simulation is performed in Matlab7.0. Mat lab has following advantages over other programming language
1) Ease of use.
2) Better Graphical User Interface
3) Platform Independent
4) Command based
5) Better debugging.

The following toolboxes are used during programming of above algorithms
1) Signal processing Toolbox.
2) Filter design toolbox.
3) General purpose commands.

Simulations were performed in the context of acoustic echo cancellation. This application is basically a system identification problem, where an adaptive filter is used to identify an unknown system, i.e., the acoustic echo path between the loud- speaker and the microphone. The measured acoustic impulse response used in simulations is depicted in Fig.6.4. 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 far-end (input) signal x(n) is either a whit gaussian noise or a speech sequence. An independent whitegaussian noise w (n), is added to the echo signalwith different values of the ENR. The performance is evaluated in terms of the normalized misalignment (in dB), defined as

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

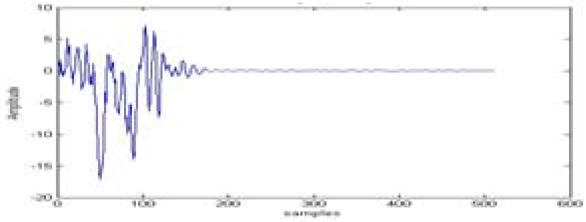

Figure 3: Acoustic impulse response used in Simulations

In order to outline the influence and the importance of the regularization parameter, the normalized step-size parameter of the adaptive algorithms is set to α=1 for most of the experiments (except when a speech sequence is used as input). In this way, we provide the fastest convergence rate for the adaptive filters, so that the difference between the algorithms (in terms of the misalignment level) is influenced only by the regularization parameter.

8. Simulation Results of NLMS Algorithm

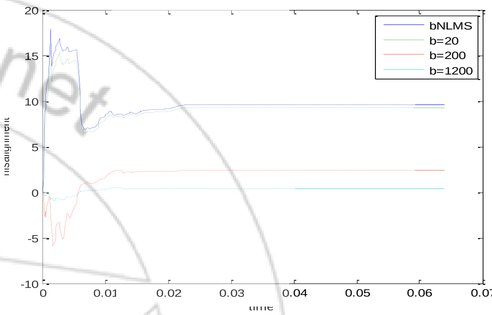

Figure 4: Misalignment of the NLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, L=512, and ENR=30dB.

In the first set of experiments, the performance of the NLMS algorithm is evaluated. Fig.6.5 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}. The ENR is setto 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.

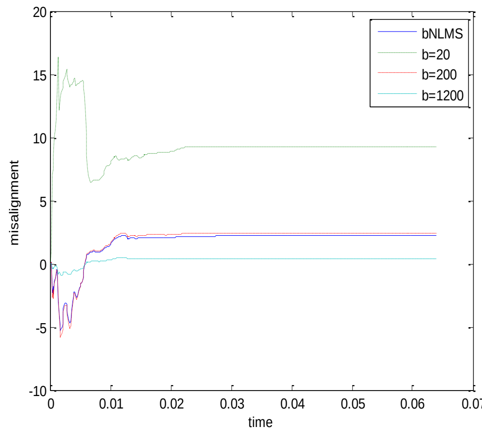

Figure 5: Misalignment of the NLMS algorithm using different values of the normalized regularization parameter.

The input signal is speech sequence, α=1, L=512, and ENR=10dB.

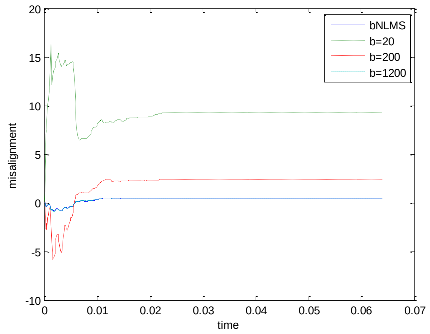

Figure 6: Misalignment of the NLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, L=512, and ENR=0dB.

The same experiment is repeated in Fig.6.5, but using a lower value of the ENR, i.e., 10dB. It is clear that the importance of the "optimal" regularization becomes more apparent. In this case, a higher value of the normalized regularization constant is required (i.e., β=200). In order to match the performance obtained with β_{NLMS} the normalized regularization constant needs tobe further increased(i.e., β=1200), if the ENR is set to 0dB..All these results are inconsistence with Fig. 6.4, which provides the values of β_{NLMS}as a function of the ENR.

9. Simulation Results of SR-NLMS Algorithm

Commonly, the SR-NLMS algorithm uses a similar regularization to the NLMS algorithm. As we already prove that the regularization parameters of these two algorithms differ by the factor β_x, i.e., $\beta_{SR\text{-}NLMS}=\beta_x\ \beta_{NLMS}$

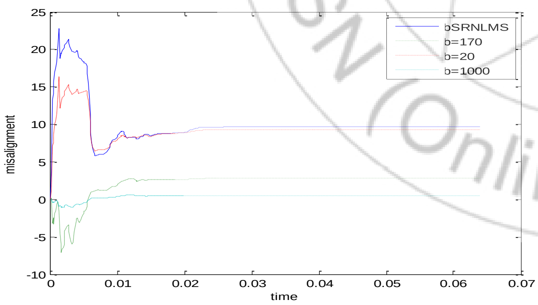

Figure 7: Misalignment of the SR-NLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, L=512, and ENR=30dB.

Fig.7 presents the misalignment of the SR-NLMS algorithm with different values of β as compared to the "optimal" normalized regularization $\beta_{SR\text{-}NLMS}$given in (4.29).The input signal is white and Gaussian, and ENR=10dB. The SR-NLMS algorithm with $\beta_{SR\text{-}NLMS}$(whichis 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.8 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.

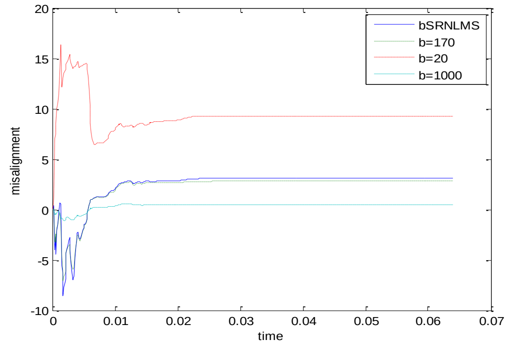

Figure 8: Misalignment of the SR-NLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, L=512, and ENR=10dB.

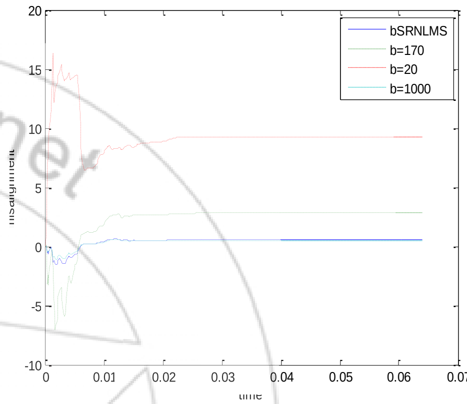

Figure 9: Misalignment of the SR-NLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, L=512, and ENR=0dB.

10. Simulation Results of Regularized IP-NLMS Algorithm

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 shouldbe taken as $\delta_{IPNLMS}=\delta_{NLMS}(1-k)/(2L)$.However, as it was proved, the regularization of the IP-NLMS algorithm does not depend on the parameter k (that controls the amount of proportionality in the algorithm). The "optimal" regularization of the IP-NLMS algorithm is equivalent to the regularization of the NLMS up to the scaling factor L, i.e, $\beta_{IPNLMS}=\beta_{NLMS}/L$.

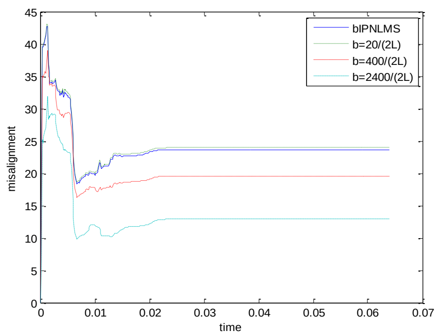

Figure 10: Misalignment of the IP-NLMS algorithm using different values of the normalized regularization parameter.

The input signal is speech sequence, α=1, k=0, L=512, and ENR=30dB.

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 constantβ=20/2L, as compared to the "optimal" normalized regularization β_{IPNLMS}. The input signal is white and Gaussian, and ENR=30dB. It can be noticed that the performance of the algorithms is very similar. However this is not the case for lower ENRs. Whenever ENR is 10dB, 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}.

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

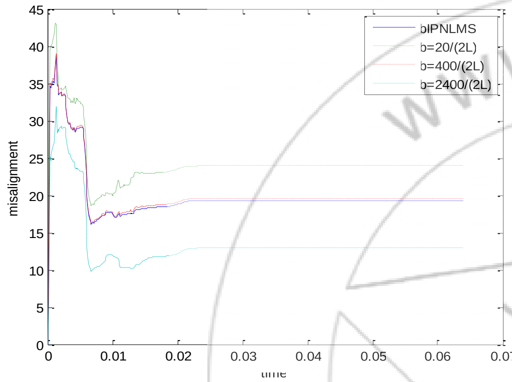

Figure 11: Misalignment of the IP-NLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, k=0, L=512, and ENR=10dB.

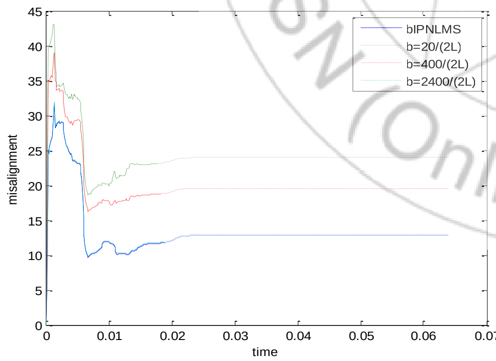

Figure 12: Misalignment of the IP-NLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, k=0, L=512, and ENR=0dB.

11. Simulation Results of Regularized SR-IP NLMS Algorithm

Finally, the performance of the SR-IPNLMS algorithm is evaluated. Usually the regularization of this algorithm is identical to the IP-NLMS one.

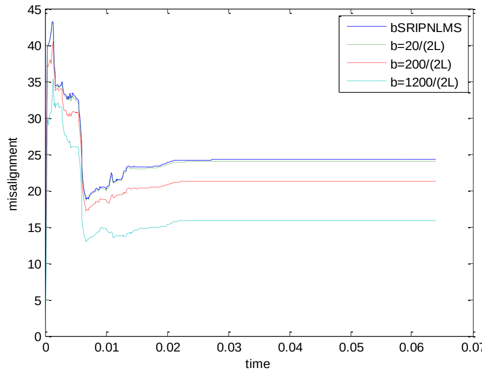

Figure 13: Misalignment of the SR-IPNLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, k=0, L=512, and ENR=30dB.

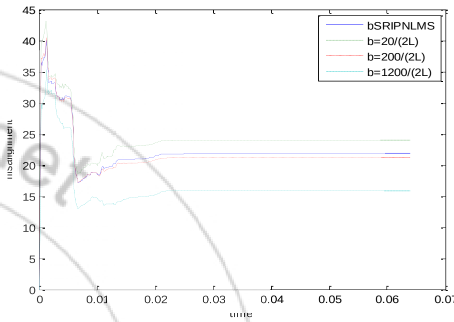

Figure 14: Misalignment of the SR-IPNLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, k=0, L=512, and ENR=10dB

The relation between the regularization parameters of the SR-IPNLMS and IP-NLMS algorithms is similar to one between the SR-NLMS and NLMS algorithms, i.e., $\beta_{SR\text{-}IPNLMS}= \beta_x\beta_{IPNLM}$. In Fig.6.15, the input signal is white and Gaussian, 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).

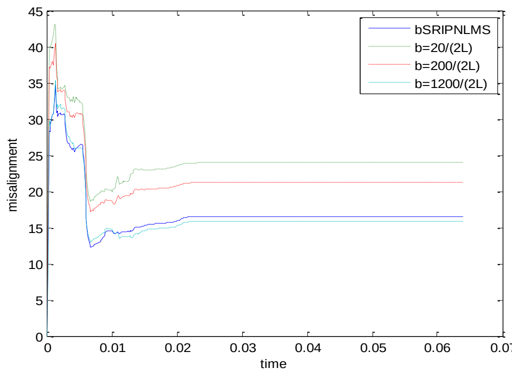

Figure 15: Misalignment of the SR-IPNLMS algorithm using different values of the normalized regularization parameter. The input signal is speech sequence, α=1, k=0, L=512, and ENR=0dB.

In Fig.14 we consider ENR=0dB and it is clearthat a higher normalized regularization parameter is required now [i.e., β=1200/(2L)] to match the performance obtained with β of SR-IPNLMS.

12. Conclusions

This paper presented novel NLMS algorithms based on the concept of regularization, which is used to solve the ill-posed problems occurred in adaptive filtering process. And in this thesis, we proposed a simple condition, for the derivation of an optimal regularization parameter. From this condition we derived the optimal regularization parameters of four algorithms: the NLMS, the SR-NLMS, the IP-NLMS, 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.

13. Future Scope

This project implements a new NLMS Algorithms based on the concept of regularization. The regularization is same importance as the step size parameter in an adaptive filter, which is clarified from this project. From the results of the project we observed that misalignment is minimum at low ENR levels but high for both IPNLMS AND SR-IPNLMS compared with SRNLMS. The misalignment levels can be minimized by properly selecting the regularization parameter. In feature by using this concept we can reduce misalignment values even the impulse response is sparse.

This algorithms has very good significance in the speech processing applications like conferencing, where more than one users trying to communicate.

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