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Denoising of Sounds of Musical Instruments by RLS Adaptive Algorithm

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Abstract: Musical instrument sound information in the form of digital signal is becoming very popular in modern communication era, but the signal obtained after transmission is often corrupted with noise. The received sound signal needs processing before it can be used for applications. Signal denoising involves the manipulation of the signal data to produce a very high quality hearing perception. In this paper we reviews the existing adaptive filter algorithms LMS, NLMS and RLS for de-noising the musical instrument sound signal and performs their comparative study. Here we introduce the variable percentage of additive white Gaussian noise (AWGN) to the sound signal and different adaptive filters are compared. It is observed that RLS algorithm performs better than the other two LMS and NLMS algorithms in terms of peak signal to noise ratio (PSNR), rate of convergence and least time for de-noising the sound signal. Hence this algorithm can also be used for real time applications. It is also observed that the sound signal de-noised with RLS algorithm is very close to the original signal.

Keywords: standard deviation of noise; PSNR; adaptive filtering; RLS; denoising;

I. INTRODUCTION

The basic idea behind this paper is the estimation of the uncorrupted musical instrument sound signal, and is also referred to as signal "denoising". There are various methods to help recover the signal from noisy distortions. Selecting the appropriate method plays a major role in getting the desired signal. The denoising methods tend to be problem specific. For example, a method that is used to de-noise the percussion instrument sound may not be used for musical melody. In order to quantify the performance of the various de-noising algorithms, a good quality signal is taken and some noise is added to it. This would then be given as input to the de-noising algorithm, which produces a signal close to the original high quality signal. The performance of the each algorithm is compared by computing peak signal to noise ratio (PSNR) besides the hearing perception.

In case of signal denoising methods, the characteristics of the degrading system and the noise is assumed to be known beforehand. The signal s(n) is degraded by a linear operation and noise N(n) is added to form the degraded signal w(n). The linear operation shown in the figure 1 is the addition of the noise to the signal [1]. Once the corrupted signal is obtained, it is subjected to the de-noising technique to get the de-noised signal z(n). Three popular adaptive filtering techniques are studied in this paper. Noise removal or noise reduction can be done on a signal by least mean square (LMS), normalized least mean square (NLMS) and recursive least square (RLS) algorithms. Each technique has its advantages and disadvantages. De-noising by these adaptive filter algorithms is recent in the field of linear filtering.

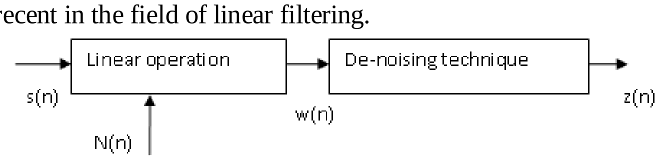

Figure 1. Concept of denoising.

Signal denoising problem is solved by the researchers by using the various techniques in the past. In [2], LMS algorithm is used to de-noise the EEG signal and gives significant improvement in SNR values over various commonly used filters such as FIR and IIR. Comparison of frequency, time frequency and adaptive methods are discussed in [3], where choice of method depends upon statistical parameters. Choice of denoising technique is also dependent upon the type of signal, 1-D or 2-D. Adaptive filter techniques are popular due to the rate of convergence and accuracy of results. In [4]-[6], adaptive filter techniques are used to de-noise the 1-D signals, which has been cause of concern in the recent past. The rest of the paper is organized as follows; Theory related to least mean square (LMS), normalized least mean square (NLMS) and RLS algorithm is briefly discussed in section 2. This section compares the differences between the above mentioned algorithms for adaptive filter design. The experimental results using above three algorithms for denoising the musical instrument sound signal are given in Section 3. Conclusions drawn along with some directions for future research are given in Section 4.

II. ADAPTIVE FILTER DENOISING

The algorithm for adaptive noise cancelation is shown in the figure 2. In this algorithm the input x(n), a noise source N1(n), is compared with a desired signal d(n), which consists of signal s(n) corrupted by another noise N2(n). The Adaptive filter coefficients adapt to cause the error signal to be a noiseless version of the signal s(n). Both the noise signals of this configuration need to be uncorrelated to the signal s(n). In addition the noise sources must be correlated to each other in some way, perfectly equal to get the best results. Due to the nature of the error signal it will never be zero, but it will converge to the signal s(n), but not to the exact signal. In other words we can say that the difference between the signal s(n) and error signal e(n) will always be positive value. The optimal solution is to minimize the difference between these two signals.

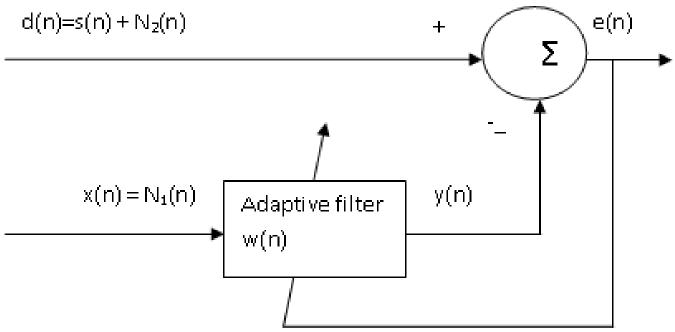

Figure 2. Adaptive filter de-noising algorithm.

A. Least Mean Square (LMS) Algorithm:

A uniform linear array with N isotropic elements, which forms the integral part of the FIR adaptive filter design is shown in [7]. The weights are computed using LMS algorithm based on minimum squared error (MSE), therefore the spatial filtering problem involves estimation of the signal s(n) from the received signal x(n) by minimizing the error between the reference signal d(n), which closely matches or has some extent of correlation with the desired signal estimate and the output y(n).From the method of steepest decent, the weight vector equation is given by [8];

$$w(n+1) = w(n) + \frac{1}{2}\mu[-\nabla(E\{e^2(n)\})] \quad (1)$$

Where μ is the step size parameter and controls the convergence characteristics of the LMS algorithm; $e^2(n)$ is the mean square error between the output y(n) and the reference signal. The LMS algorithm is initiated with an arbitrary value w(0) for the weight vector eventually leads to the minimum value of the mean squared error. Since w(n) is a vector of random variables, the convergence of the LMS algorithm [9] should be considered within the statistical framework. For the convergence of the algorithm the step size should satisfy the following condition;

$$0 < \mu < \frac{2}{\lambda max} \quad (2)$$

Where λmax is the largest eigenvalue of the correlation matrix. The drawback of the LMS algorithm is its sensitivity to the change in the input signal x(n), which result in finding difficulty to decide the optimum size of convergence parameter μ for convergence of the algorithm along with minimum time of convergence.

B. Normalized Least Mean Square (NLMS) Algorithm:

Normalized Least Mean Square (NLMS) is actually derived from LMS algorithm. The need to derive NLMS algorithm is that the input signal power changes in time and due to this change, the step size between two adjacent coefficients of the filter will also change, due to which it affects the convergence rate. For week signals this convergence rate will slow down, and for strong signals convergence rate will be increased, hence producing error. To overcome this problem of convergence rate, we try to adjust the step size parameter with respect to input signal power, therefore the step size parameter is said to be normalized. This algorithm may be a suitable alternative which normalizes the LMS step size with the power of the input signal [10]. When the input signal is too small, the NLMS algorithm can be modified by adding a small positive value δ to the power of the input signal. Hence,

$$w(n+1) = w(n) + \beta \frac{x^*(n)}{\delta + |x(n)|^2} e(n) \quad (3)$$

Where β is normalized step size, whose value is $0 < \beta < 2$, and δ is safety factor whose value is always lesser than one. So the problem of sensitivity of step size is resolved with NLMS algorithm.

C. Recursive Least Square (RLS) Algorithm:

The RLS adaptive filter is the time update version of wiener filter [11]. For non stationary signals, this filter tracks the time variations but in case of stationary signals, the convergence behavior of this filter is the same as wiener filter that converges to the same optimal coefficients. This filter has fast convergence rate and it is widely used in various signal processing applications where the signal chances very fast. This adaptive algorithm is computationally complex and has high speed of convergence, minimum error at convergence, numerical stability and robustness. The RLS algorithm is executed in the following way;

a. Choose λ =0.99 (always less than 1) and initialize the value of the weight vector as zero, w(0)=0; then, the gain vector is given as,

$$K(n) = \frac{\lambda^{-1} P(n-1)u(n)}{1 + \lambda^{-1}u^H(n)P(n-1)u(n)} \quad (4)$$

b. Compute the error vector given by,

$$e(n) = d(n) - u^H(n)w(n-1) \quad (5)$$

c. Update the estimate of coefficient value,

$$w(n) = w(n-1) + K(n)e^*(n) \quad (6)$$

d. Take the inverse of weighted autocorrelation matrix $P(n)$, given by,

$$P(n) = \lambda^{-1}P(n-1) - \lambda^{-1}K(n)u^H(n)P(n-1) \quad (7)$$

Each time the value of n is incremented and the steps 1- 4 are repeated until the minimum value of the error is achieved.

III. RESULTS AND DISCUSSIONS

The various adaptive noise cancelation algorithms discussed in the previous section are applied to the samples of sound produced by Indian musical instruments sampled at 44.1K samples per second. For experimental purpose the sounds of three musical instruments shehnai, dafli and flute are taken. The performance of LMS, NLMS and RLS algorithms is compared on the basis of mean square error along with the various percentage of Gaussian noise introduced in the signal. The percentage of Gaussian noise is dependent upon the value of standard deviation σ. For comparing the performance and measurement of quality of de-noising, the peak signal to ratio (PSNR) is determined between the original signal S_i and the signal de-noised S_d , by adaptive algorithms. The PSNR value is calculated as follows;

$$\mathrm{PSNR} = 10 \log_{10}\left(\frac{\mathrm{S_{max}}^2}{\mathrm{MSE}}\right) \quad (8)$$

Where S_{max} is the maximum value of the signal and is given by,

$$S_{max} = \max(\max(S_i), \max(S_d)) \tag{9}$$

And MSE is Mean Square error given by,

$$MSE = \frac{1}{N}\sum_{l=1}^{N}[S_d(l) - S_i(l)]^2 \tag{10}$$

Where N is the length of the signal. The PSNR values obtained from LMS, NLMS and RLS algorithms at various percentage of introduced noise to shehnai, dafli and flute signals are shown in tables 1, 2 and 3.

Table: 1 PSNR values obtained after de-noising shehnai sound

Standard deviation (σ)	LMS	NLMS	RLS
0.01	24.15	24.71	36.69
0.02	24.18	24.95	34.14
0.03	23.98	24.90	29.51
0.04	24.37	24.86	28.69
0.05	24.28	24.61	30.05
0.06	23.91	24.85	27.79
0.07	24.46	24.69	28.07
0.08	23.72	24.51	31.90
0.09	24.27	25.30	30.34
0.10	23.87	25.28	27.34

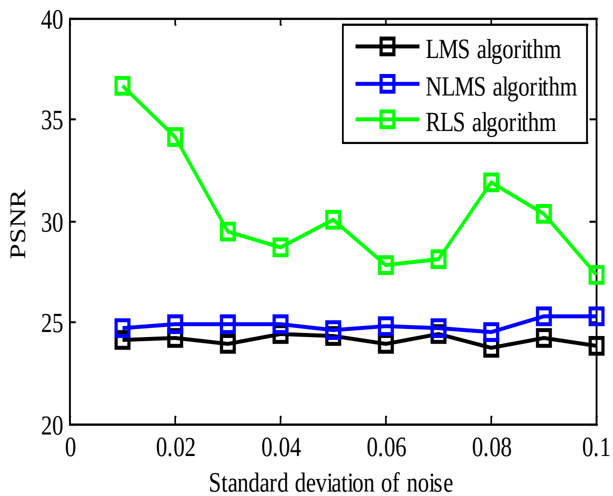

Figure 3. PSNR values of adaptive algorithms for shehnai sound.

Table: 2 PSNR values obtained after de-noising dafli sound

Standard deviation (σ)	LMS	NLMS	RLS
0.01	30.19	28.81	41.71
0.02	30.93	28.02	43.52
0.03	31.48	28.57	38.81
0.04	28.21	27.33	38.43
0.05	30.43	26.35	37.80
0.06	27.73	24.17	35.12
0.07	29.84	24.78	35.70
0.08	29.89	25.26	36.16
0.09	27.90	24.69	33.19
0.10	29.94	23.86	32.31

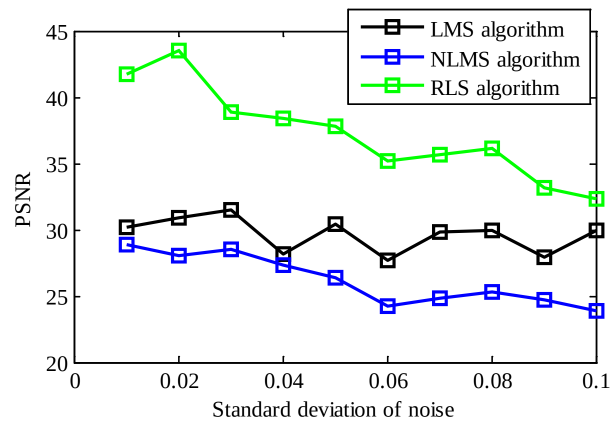

Figure 4. PSNR values of adaptive algorithms for dafli sound.

Table: 3 PSNR values obtained after de-noising flute sound

Standard deviation(σ)	*LMS*	*NLMS*	*RLS*
0.01	12.92	13.09	17.34
0.02	12.93	12.90	15.71
0.03	12.97	13.10	15.51
0.04	12.91	12.76	14.39
0.05	12.93	12.81	13.83
0.06	12.99	13.16	14.85
0.07	13.02	13.07	14.23
0.08	12.90	12.88	13.71
0.09	12.98	12.97	13.41
0.10	12.90	12.93	16.24

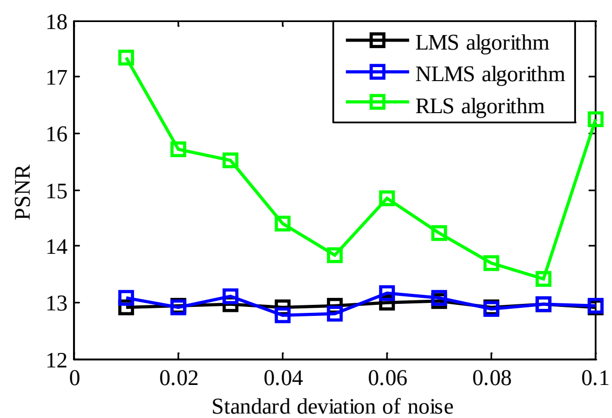

Figure 5. PSNR values of adaptive algorithms for flute sound.

The number of iterations used for de-noising the signal is least in case of RLS algorithm, hence the computation time also. The computation time for execution of different algorithms for various signals is shown in table 4.

Table: 4 De-noiding time for different algorithms in sec

Sound signal	*LMS*	*NLMS*	*RLS*
shehnai	424.25	436.45	20.86
flute	161.93	167.58	13.50
dafli	82.46	86.93	9.87

It is observed from the figures 3, 4 and 5 that the PSNR value obtained using RLS algorithm is maximum as compared to LMS and RLS algorithm. Hence the signal de-noised with RLS algorithm will be close to the original signal, which can be verified by hearing perception. The musical instrument sound signal de-noised with RLS algorithm is shown in the figure 6, 7 and 8.

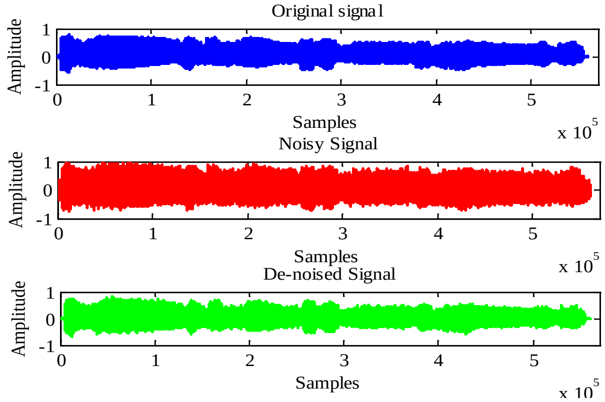

Figure 6. Original, noisy and RLS de-noised shehnai sound.

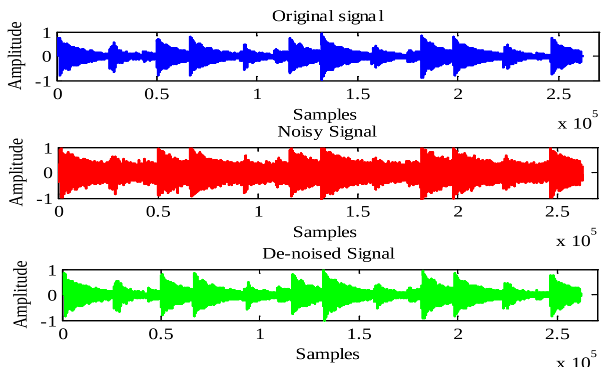

Figure 7. Original, noisy and RLS de-noised dafli sound.

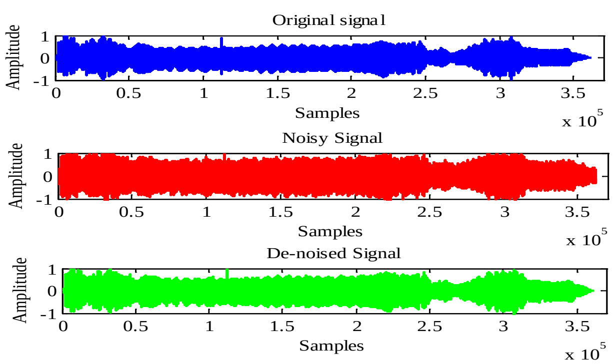

Figure 8. Original, noisy and RLS de-noised flute sound.

IV. CONCLUSIONS

LMS, NLMS and RLS are three adaptive algorithms which are used for de-noising the sounds of musical instruments. Among the three NLMS and RLS are not sensitive to step size, hence they are more accurate and converges very fast. It is observed from the result obtained previously that RLS algorithm performs better than other algorithms with respect to the speed of convergence, accuracy, minimum mean square error and PSNR values. The PSNR values obtained through RLS algorithm are much higher than the other two algorithms, and the time of denoising is very less. Hence we can use RLS algorithm for de-noising the musical instrument sound signal for real time applications also. The hearing perception of the de-noised signal with this algorithm is closer to the original signal. This work can be extended by comparing wavelet techniques with adaptive methods for denoising.

V. REFERENCES

[1] J. N Lin, X Nie and R. Unbehauen, “Two dimentional LMS adaptive filter incorporating a local mean estimator for image processing,” IEEE Transaction of Circuit and Systems-II: Analog and digital Signal Processing, Vo. 40, No. 7, pp. 417-428, July 1993.

[2] N. V Thakur and Y. S Zhu, “Applications of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection,” IEEE Transaction on Biomedical Engg., Vol. 38, pp. 785-794, 1991.

[3] M. Alam, M. I Islam and M. R Amin, “Performance comparison of STFT, WT, LMS and RLS adaptive algorithms in Denoising of speech signals”, International Journal of Engineering and Technology, Vol. 3, No. 3, pp. 235-238, June 2011.

[4] S. Ikeda and A. Sugiyama, “ An adaptive noise canceller with low signal distortion for speech codes,” IEEE Transaction on Signal Processing, Vol. 47, pp. 665-674, March 1999.

[5] J. E Greenberg, “ Modified LMS algorithms for speech processing with an adaptive noise canceller,” IEEE Transaction on Speech and Audio processing, Vol. 6, No. 4, July 1998.

[6] R. Sharma, and V. P Pyara, “A comparative analysis of mean square error adaptive filter algorithms for generation of modified scaling and wavelet function,” International Journal of Engineering Science and technology, Vol. 4, No. 4, pp.1396-1401, April 2012.

[7] M. Tarrab, and A. Feuer, “Convergence and Performance Analysis of Normalized LMS Algorithm with Uncorrelated Gaussian Data,” IEEE Transaction on Information Theory, vol. 34, pp. 680-691, 1988.

[8] S. C Douglas, and R. Markus, “Convergence issue in the LMS adaptive Filter,” CRC press LLC, 2000.

[9] R. Markus, “The Behavior of LMS and NLMS Algorithms in the Presence of Spherically Invariant Process,” IEEE Transactions on Signal Processing, Vol.41, No.3, pp. 1149-1160, 1993.

[10] Dirk, T.M. Slock, “On the Convergence Behavior of LMS and Normalized LMS Algorithm,” IEEE Transactions on Signal Processing, Vol.41, No.9, pp. 2811-2825, 1993.

[11] B. B Farhang, “Adaptive Filter Theory and Applications,” John Wiley and Sons, New York.

