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System Identification in Speech Signal Using Modified Kalman Based Normalized Least Mean Square (NLMS) Algorithm

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Abstract— In this paper a modified Kalman based normalized least mean square algorithm is proposed for system identification. The performance of the proposed algorithm is compared with normalized least mean square (NLMS) and original Kalman based normalized least mean square (KLMS) algorithm using standard IEEE sentence (SP23) of NOIZEUS database with different types of real world noises at different SNR. The proposed algorithm shows better output SNR and speed of convergence compared with NLMS and KLMS algorithm

Keywords— System Identification, NLMS, Kalman filter , KLMS, SNR.

I. INTRODUCTION

The quality and intelligibility of speech reduced at the receiving end when the input speech is mixed with some form of the noise components. So the original speech becomes unpleasant to listen. The amount of unpleasant is depending upon the type of noise corrupted to the speech signal. The quality and intelligibility of the speech in the presence of background noise can be improved by speech enhancement algorithms. Over many decades researchers are focused in this area and developed the different algorithms to remove the noise which is present along with the speech signal. [4-8] To suppress the backhgrount noise still adaptive filter is better tool. In the basic adaptive filter like least mean square (LMS) algorithm the step size remains constant in updating filter coefficient equation for all the input samples [1, 2]. The basic block diagram of adaptive transversal filter for system identification is shown in Figure 1. in which input signal $u(n)$ consists of desired signal with noise determines the filter coefficient "w", that minimizes the error $e(n)$, between the output of the filter $y(n)$, and the desired signal d(n).The basic Least Mean Square(LMS) algorithm suffers from fixed step size problem. But in normalized LMS (NLMS) algorithm the weight vector changes along with the input, so the step size keeps on adjusting from one iteration to the next iteration. The rate of convergence of NLMS algorithm is faster than that of LMS filter.[1] So the method of varying the step size is focused by many researchers and develops the different forms of NLMS algorithms

In which Kalman based normalized algorithm (KLMS) is also one among them. The proposed algorithm is modification of KLMS algorithm, which clearly shows improvement in output SNR compared with NLMS and KLMS for different types of noises at different levels of input SNR.

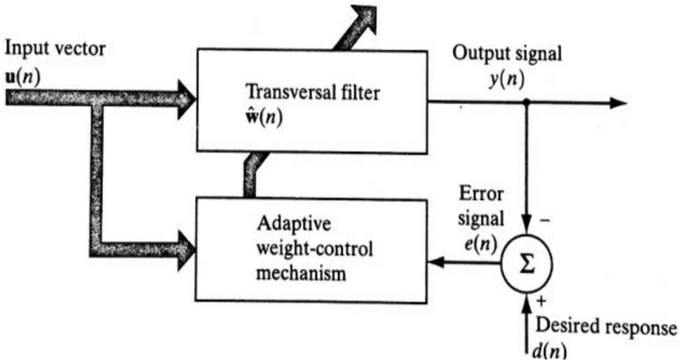

Figure 1. Adaptive transversal filter

II. ADAPTIVE ALGORITHM

The output, error and weight equation of conventional NLMS algorithms are shown below.

The output; $y(n)=w(n).u^T(n)$ (1)

The error; $e(n)=d(n)-y(n)$ (2)

The weight equation:

$$w(n+1) = w(n) + \frac{\mu}{\acute{\varepsilon}+|u(n)||^2} u(n)\, e(n) \qquad (3)$$

Where 'w' is the adaptive filter vector weight and $|u(n)||^2$ is equal to $u(n)*u^T(n)$, small const (ɛ́) is used in the denominator to prevent the division by a very small number and 'μ' is constant.

III. KALMAN FILTER

The Kalman filter is a mathematical procedure based on steady-state approach which operates through a prediction and correction mechanism. The block diagram of Kalman estimator is shown in Figure2 [1]. In Kalman filter, the dynamics of the signal generation process is being modeled by state equation. The noisy and distorted components will be modeled by observation equations [6-8], so it acts as recursive data processing algorithm. Hence it can be used for cancelling stationary and nonstatioinary noise. The two major states of Kalman filter are "Predict" and "Update". Predict phase estimate the current time state by using previous time step, without using the current observation information of the current time step. In the update state current priori prediction is done using current observation information to refine the state estimate.

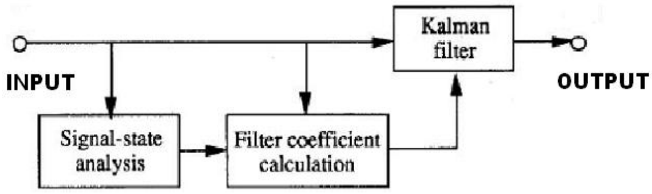

Figure 2 Block diagram of Kalman estimator for noise

Order update and time update equations for Kalman filter are shown below.

$x(n+1)=F(n)x(n)+n(n)$ (4)

$z(n)=H^T(n)x(n)+v(n)$ (5)

where x(n) is the state vector of the system, Z(n) is measured signal vector, F(n) is state transition matrix, n(n) is the state noise, H(n) is the observation matrix and v(n) is the measurement noise. The state noise and measurement noise are assumed to be Gaussian random variables with known autocorrelation functions.

The autocorrelation of the state noise and the measurement noise are given by Qnn(n)&Qvv(n).

$Qvv(n) = E[v(n)\, v^T(n)]$ (6)

$Qnn(n) = E[n(n)\, n^T(n)].$ (7)

Initialize

$\hat{x}|_0(0) = \hat{x}_{0|0}$ (8)

$\Sigma x|_0(0) = \Sigma_{x|0}$ (9)

Iterate from n = 1 to…

$\alpha(n) = z(n) - H^T(n)\, \hat{x}|_{n-1}(n)$ (10)

Order update

$K(n) = \Sigma_{x|n-1}(n)H(n)\, (H^T(n)\Sigma_{x|n-1}(n)H(n) + Q_{vv}(n))^{-1}$ (11)

$\hat{x}|_n(n) = \hat{x}|_{n-1}(n) + K(n)\alpha(n)$ (12)

$\Sigma_{x|n}(n) = \Sigma_{x|n-1}(n) - K(n)H^T(n)\Sigma_{x|n-1}(n)$ (13)

Time update

$\hat{x}|_n(n + 1) = F(n)\hat{x}|_n(n)$ (14)

$\Sigma_{x|n}(n + 1) = F(n)\Sigma_{x|n}(n)F^T(n) + Q_{nn}(n)$ (15)

Where,

$\hat{x}(n|n)$- Estimate of x(n) given measurements z(n), z(n-1)

$\hat{x}(n+1|n)$- Estimate of x(n+1) given measurements z(n), z(n-1)

$\Sigma_{x|n(n)}$ is state covariance matrix and updates for each iteration.

IV. KLMS ALGORITHM

If Kalman filter is modified as an adaptive filter then the adaptive filtering become state estimation, where the state vector corresponds to filter coefficients of an adaptive filter. The square of the error of each coefficient is minimized in state estimation. Hence output error also reduces [3]. This links Kalman filter with LMS algorithm and extracts the advantages of both.

Many researchers are focusing to develop Kalman based adaptive algorithm in which Kalman based normalized LMS (KLMS) [5] is one among them, Table1 shows the transition of parameters from Kalman filter to normalized LMS algorithm. Where state transition matrix F(n) = λ I with λ close to one.

Table 1: Transition of Kalman filter variables to NLMS variables

Kalman	Kalman LMS
z(n)	d(n)
H(n)	u(n)
x|n(n)	w(n)
Σx|n−1(n)	Σw(n)
Qnn(n)	Qnn(n)
Qvv(n)	qv(n)
F(n)	λ I

The system of equations for normalized Kalman filter is shown below.

Initialize

$w(0) = w_0$ (16)

$\sigma^2 w(0) = \sigma^2 w_0$ (17)

Iterate from n = 0 to...

$P(n) = u^H(n)u(n)$ (18)

$\alpha(n) = d(n) - u^T(n)w(n)$ (19)

$$w(n+1)=w(n) + \frac{u(n)*\alpha(n)}{P(n) + qv(n)/\sigma^2 w0(n)} \quad (20)$$

$$\sigma^2_w(n+1)=\sigma^2_w(n)\left(1 - \frac{P(n)/N}{P(n)+qv(n)/\sigma^2 w(n)}\right)+q_n(n) \quad (21)$$

Where $q_v(n)$ and $q_n(n)$ measurement noise and state noise respectively.

V. PROPOSED METHIOD

For the speech signal the state noise $q_n(n)$ is very low or zero, total power $P_T(n+1)= P_T(n)+ P(n)$. $F(n) = \lambda$ I and if λ=1, then the ratio of measurement noise to state covariance matrix is assumed to be constant for all the input speech samples then the denominator term $qv(n)/\sigma^2 w(n)$becomes constant and replaced by'$\acute{\varepsilon}$'. Then the equation (21) becomes

$$w(n+1)=w(n) + \frac{u(n)*\alpha(n)}{P(n) + PT(n)/N+\acute{\varepsilon}} \quad (22)$$

The proposed algorithm is similar to NLMS algorithm but gives improvement in SNR, improves convergence and also stable because which is derived from Kalman filter.

VI. SIMULATED RESULTS

The simulations are carried with standard IEEE sentence sp23(NOIZEUS database) of male voice saying"stop whistling and watch the boys march". The original signal has 21209 samples. 'q_v' is assumed to be $0.25)^2$and q_n=0. The constant '$\acute{\varepsilon}$' is experimentally found to be 0.01 for better response with filter order 8. The performance of the NLMS, KLMS and proposed method are tested with babble noise, restaurant noise, airport noise and train noise at different level of SNR taken from AURORA data base. The Figure 3 shows the desired signal, signal+noise, output and the mean square error for NLMS with original speech corrupted with babble noise of' 0'dB and Figure 4 shows the same for KLMS and Figure 5 shows for proposed method. Table 2 demonstrates the performance of output SNR for different methods. The proposed method gives better output SNR for all types of nonstationary noises at different level of input SNR andalso reduces mean square error compared to other methods.The mean square error for NLMS, KLMS and modified algorithms are -27.89 dB, -28.43dB and -29.87dB respectively

VII. CONCLUSION

In this paper modified KLMSalgorithm is proposed and results are demonstrated for different types of nonstationary noises at different levels. The proposed algorithm gives better output SNR and reduces mean square error due to estimated weight of the unknown system matching with actual weight of the desired signal.Convergence rate is also very high and stability is also good because the algorithm is derived using principles of Kalman filter. This algorithm can be used in echo cancellation, noise cancellation in public speech and also in digital hearing aids.

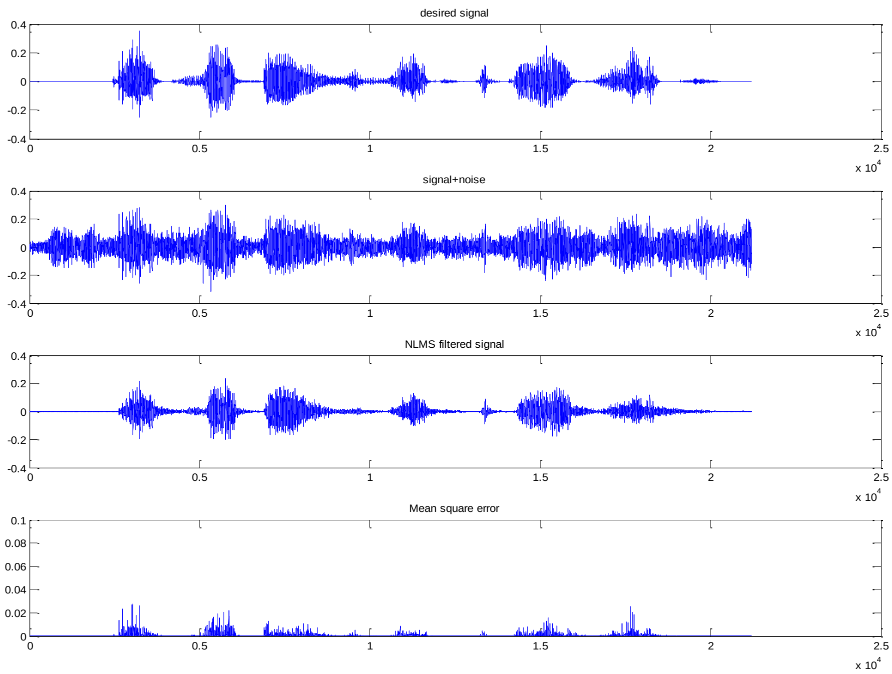

Figure 3 The desired signal, signal+noise, output and the mean square error for NLMS with '0' dB Babble noise

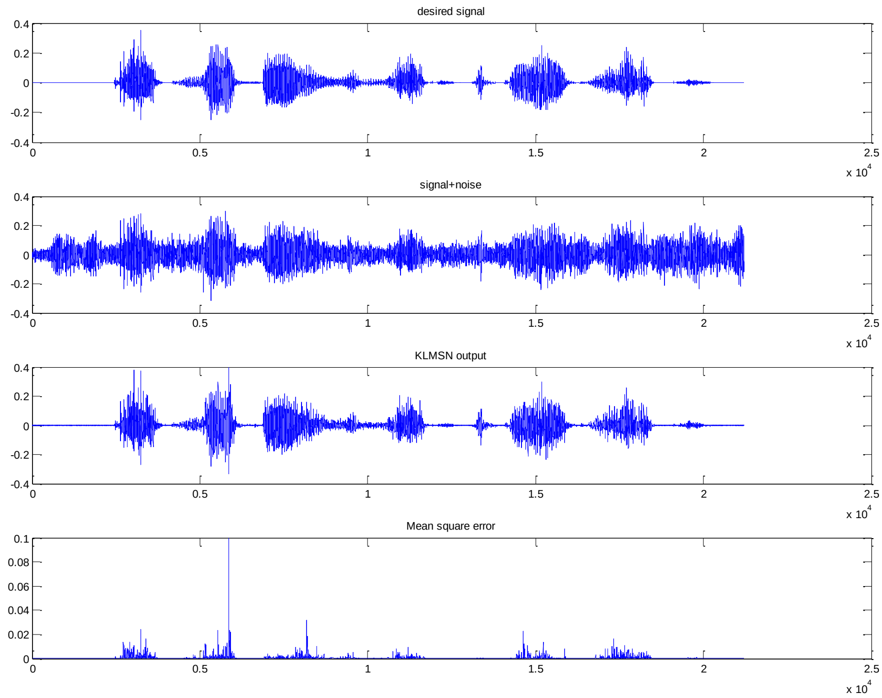

Figure 4 The desired signal, signal+noise, output and the mean square error for KLMS with '0' dB Babble noise

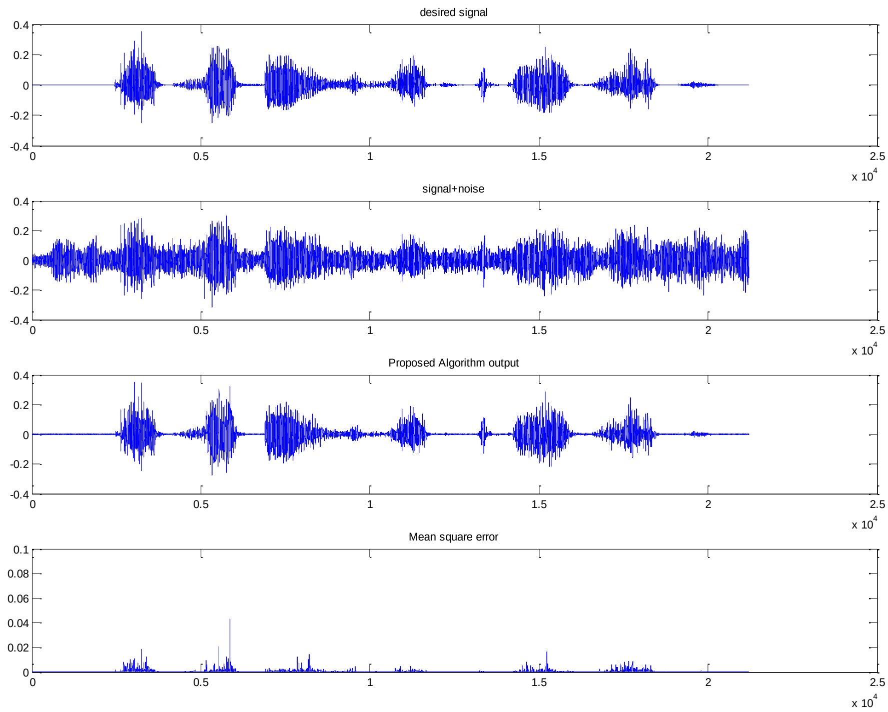

Figure5 The desired signal, signal+noise, output and the mean square error for proposed algorithm with '0' dB Babble noise

Table:2 Performance of various algorithms for different types of noises at different input SNR

Type of Noise	**input File name**	**Input SNR in dB**	**Output SNR in dB**		
			NLMS	**KLMS**	**Proposed Method**
Babble Noise	sp23_babble_sn0	0	5.25	6.57	8.06
	sp23_babble_sn0	5	7.69	9.14	10.96
	sp23_babble_sn0	10	10.70	13.67	14.81
	sp23_babble_sn0	15	12.86	16.75	18.09
Restaurant Noise	sp23_resturant_sn0	0	4.91	5.76	7.14
	sp23_resturant_sn5	5	7.26	8.49	10.38

	sp23_resturant_sn10	10	11.02	13.56	15.30
	sp23_resturant_sn15	15	12.24	16.75	17.84
Airport Noise	sp23_airport_sn0	0	4.39	4.82	6.89
	sp23_airport_sn5	5	7.55	8.95	10.56
	sp23_airport_sn10	10	10.04	12.69	14.15
	sp23_airport_sn15	15	12.87	17.29	18.52
Train Noise	sp23_train_sn0	0	5.50	6.28	7.49
	sp23_train_sn5	5	8.53	9.36	10.88
	sp23_train_sn10	10	10.69	12.15	13.89
	sp23_train_sn15	15	12.92	16.72	17.98
Exhibition Noise	sp23_exhbition_sn0	0	5.39	5.64	6.77
	sp23_exhbition_sn5	5	7.87	8.62	10.03
	sp23_exhbition_sn10	10	10.45	12.33	13.92
	sp23_exhbition_sn15	15	12.50	16.17	17.51

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