ACOUSTIC NOISE CANCELLATION USING ROBUST RLS ALGORITHM: A COMPARATIVE RESULT ANALYSIS

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ABSTRACT

In Aircraft Cabin, Hands-Free Telephones and Teleconferencing Systems, Noise Cancellers are required, which are often implemented by adaptive filters. The correlation between input & noise will slow down the convergence rate of adaptive noise canceller. The new Robust RLS algorithm which proposed here gives the minimization of cost function subject to a time-dependent constraint on the norm of the filter update. We also present some theoretical results regarding the asymptotic behaviour of the various algorithms which gives comparative results for Noise cancellation. The New Robust Recursive Least Square Algorithm (RRLS Algorithm) offers a good solution to this problem because of its regular adaptation of regularization parameter. RRLS is an adaptive scheme in which regularization parameter is varying by using L1 Norm. The Performance of the proposed scheme will evaluate in the context of adaptive noise canceller.

KEYWORDS: *Noise canceller, Adaptive Algorithm: LMS, RLS, RRLS Algorithm, Regularizing parameter, forgetting factor, noisy system.*

I. INTRODUCTION

A common problem encountered in aircraft cabin, hands-free telephones and teleconferencing systems is the presence of echoes which are generated acoustically via the impulse response of a room or cabin. Removal of these echoes requires the precise knowledge of the impulse response of the noisy path, which may be time varying. in recent years, there has been a great interest in the use of adaptive filters for cancellation of noise component which is overlap with unrelated signal in the same frequency range adaptive filter is that it uses the filter parameters of a moment ago to automatically adjust the filter parameters of the present moment, to adapt to the statistical properties that signal and noise unknown or random change, in order to achieve optimal filter [5].

Adaptive filter gives a good approach for noise cancelation by continuously updating its weight. In this way LMS algorithm gives good results with fast convergence speed [4], and letter on it is implemented with some variation in stepping factor [6] . the updating will followed using forgetting factor in RLS algorithm[7] where a trade off is required between convergence speed & Mean Square Error which can be overcome by using robust approach in which a system is updated regularly by varying its regularization parameter[8] & applied for system identification . In this paper the same approach is used for acoustic noise cancellation in which by updating regularization parameter by means of updated weights gives good results comparatively to all above mentioned algorithms.

As shown in fig. 1, the main signal d(n) picked up by the main sensors contains useful signal s(n) and interference signal v(n). In order to remove noise from the main signal, make use of the reference sensors to pick up related noise and use for the input x (n) of adaptive filter. Because of s(n)and v'(n) are not relevant, adaptive filter can only adjust reference noise v'(n) to generate similar noise v(n) of y(n). Then y(n) to eliminate the noise component y(n)in the main signal, signal e(n) gradually converge to the noise-free signal s(n) of the approximate signal[3]. In place of these two sensors should be very careful so that the noise component v (n) and highly relevant, but not perceived reference sensor signals s (n). Then these two conflicting objectives, there are some compromise. For example, an increase v (n) and relevance of the simple method is very close to the two sensors to put together. Unfortunately, this arrangement will increase to leak information in the signal of sensors.

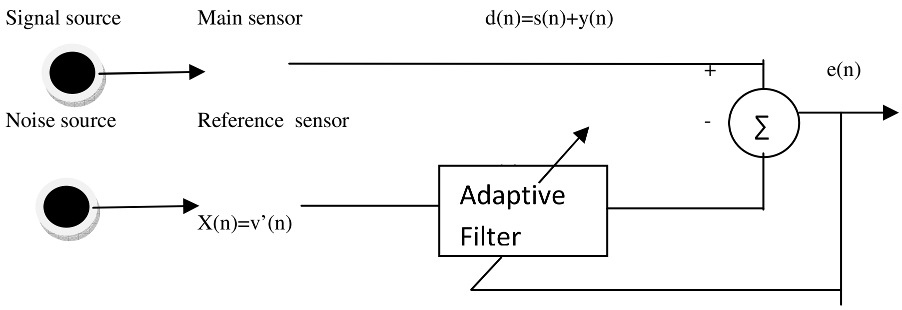

Fig. 1: Adaptive noise canceller

Adaptive noise elimination includes the elimination of all forms of interference noise. The correlation between input & noise will slow down the convergence rate of adaptive noise canceller if the RLS-Based adaptive filter is used to remove noise. A New Robust RLS Adaptive-Filtering Algorithm yields an optimal solution of the weighted least squares optimization problem. The proposed algorithm is robust with respect to acoustic noise as well as long bursts of impulsive noise in the sense that it converges back to the steady state much faster than during the initial convergence. It also tracks sudden system disturbances by adaptively varying the regularization parameter. Simulation results show that the proposed algorithm achieves improved robustness and better tracking as compared to the conventional RLS or LMS reported in [7]. The Paper Is Organized As Follows. In Section II, The Proposed Robust RLS Algorithm Is Described. In section III computational complexity is calculated. Section IV contains simulation results and finally conclusions are drawn in section V.

II. PROPOSED ROBUST RLS ALGORITHM FOR STATIONARY ENVIRONMENTS

Weighted least-squares algorithms obtain the w_k optimal coefficient vector at k iteration by solving the Optimization Problem

$$\text{minimize}_{w_k} \sum_{i=1}^{k} q_i (d_i - w_k^T x_i)^2 \quad (1)$$

Where d_i is the desired signal, x_i is the input signal vector, and q_i is a nonnegative weight at iteration i. Each of vectors w_k and x_i is of dimension m. The solution of (1) is achieved by solving the normal equations which are obtained by setting the gradient of the objective function in (1) with respect w_k to zero. The input-signal autocorrelation matrix r_k , and p_k cross correlation vector, at iteration k are given by

$$R_k = \lambda_f R_{k-1} + \delta_k x_k x_k^T \quad (2)$$

$$p_k = \lambda_f p_{k-1} + \delta_k x_k d_k \quad (3)$$

Where R_k and p_k are of dimensions [M, M] and M Respectively, and $0 << \lambda_f < 1$. Parameter λ_f Is a Pre specified fixed forgetting factor and δ_k is a nonnegative scalar. The normal equations of (1) can be expressed in matrix form as

$$R_k w_k = p_k \quad (4)$$

Using The Matrix Inversion Lemma [1], [2] In (2), we obtain the update equation of the inverse of the autocorrelation matrix as

$$S_k = \frac{1}{\lambda_f}\left(S_{k-1} - \frac{1}{\frac{\lambda_f}{\delta_k} + x_k^T S_{k-1} x_k} S_{k-1} x_k x_k^T S_{k-1}\right) \quad (5)$$

Now Using (5) in (4), the update equation of the coefficient vector is obtained as

$$w_k = w_{k-1} + \frac{1}{\frac{\lambda_f}{\delta_k} + x_k^T S_{k-1} x_k} S_{k-1} x_k e_k \tag{6}$$

Where $e_k = d_k - w_{k-1}^T x_k$ (7)

Is the *A Priori* Error. In impulsive-noise environments, the norm of the *Gain Vector*, I.E., $p_k - \lambda_f p_{k-1}$ given by

$$\left\| p_k - \lambda_f p_{k-1} \right\|_1 = \left\| \delta_k x_k d_k \right\|_1 \tag{8}$$

Undergoes a sudden increase when is corrupted by impulsive noise. As a result, the L_1 norm of p_k is also increased which would, in turn, increase the L_1 norm of w_k in (4). The effect of impulsive noise on (3) caused by d_k can be suppressed by imposing a time-varying upper bound γ_k on the L_1 norm of the gain vector in (8). In other words, we choose δ_k such that the update of the cross correlation vector in (3) satisfies the condition

$$\left\| p_k - \lambda_f p_{k-1} \right\|_1 \le \gamma_k \tag{9}$$

Parameter is chosen as

$$\gamma_k = \frac{d_k}{e_k} \tag{10}$$

For all k on the basis of extensive simulations. The condition in (9) is satisfied if is chosen as

$$\delta_k = \frac{1}{\left\| x_k e_k \right\|_1} \tag{11}$$

As can be seen, δ_k can be greater than unity which would affect the convergence performance of the adaptive filter. To circumvent this problem, we use

$$\delta_k = \min(1, \frac{1}{\left\| x_k e_k \right\|_1}) \tag{12}$$

With δ_k =1, the update equations in (5) and (6) become identical with those of the conventional RLS adaptation algorithm. The value of given by (12) will also bound the norm of the *Gain Matrix*, I.E., $R_k - \lambda R_{k-1}$ Given By

$$\left\| R_k - \lambda R_{k-1} \right\|_1 = \left\| \delta_k x_k x_k^T \right\|_1 = \min(\left\| x_k \right\| \infty \left\| x_k \right\| 1, \frac{\left\| x_k \right\| \infty}{e_k}) \tag{13}$$

For a noise corrupted, the norm of the *gain matrix* would be significantly reduced. Since the probability that δ_k =1 during the transient state is high and the convergence of the RLS algorithm is fast, the initial convergence of the proposed robust RLS algorithm would also be fast. In addition, the proposed robust RLS algorithm would work δ_k =1 with during steady state as the amplitude of the error signal, e_k becomes quite low during steady state. Consequently, the steady-state misalignment of the proposed robust RLS algorithm would be similar to those of conventional RLS adaptation algorithms. However, when an impulsive noise-corrupted e_k occurs we obtain $d_k \approx e_k$ *and* $\delta_k = \frac{1}{\left\| x_k e_k \right\|_1}$ which would force the L_1 norm of the gain vector in (8) and the norm of the *Gain Matrix* in (To Be bounded by $\gamma_k \approx 1$ and, $\left\| x_k \right\| \infty / e_k$ respectively. As a result, the norm of the coefficient vector in (4) would also remain bounded as discussed below.

The L_1 norm of the differential-coefficient vector w_k of the Conventional RLS Algorithm given by

$$\Delta w_k = w_k - w_{k-1} \tag{14}$$

Is obtained as

$$
\begin{aligned}
&\lambda_k = \lambda_f \\
&\|x_k\|_1 = \|x_{k-1}\|_1 + |x_k| - |x_{k-M}| \\
&\delta_k = \min\left(1, \frac{1}{\|x_k\|_1 \, |e_k|}\right) \\
&if\ \delta_k = 1 \\
&\|\Delta w_k\|_1 = \frac{|e_k| \, \|S_{k-1} x_k\|}{\|\lambda + x_k^T S_{k-1} x_k\|_1} \\
&else \\
&\|\Delta w_k\|_1 = \frac{\|\|S_{k-1} x_k\|_1}{\|x_k\|_1 \, \|\lambda + x_k^T S_{k-1} x_k\|_1} \\
&end
\end{aligned} \tag{15}
$$

By Using (6) In (14) With δ_k =1. As can be seen, the L_1 norm of the differential-coefficient vector in the Conventional RLS Algorithm Increases Abruptly for an impulsive noise corrupted. Similarly, the L_1 norm of the differential-coefficient vector in the proposed robust RLS algorithm for the case of an impulsive noise corrupted error signal, e_k , is obtained by using (11) and
(6) In (14) as

$$\|\Delta w_k\|_1 = \frac{\|\|S_{k-1} x_k\|_1}{\|x_k\|_1 \, \|\lambda + x_k^T S_{k-1} x_k\|_1} \tag{16}$$

As can be seen, the L_1 norm given by (16) would be much less than that in (15) since e_k cannot perturb S_{k-1}. Although δ_k would become less than one in such a situation, its effect is significantly reduced by $\|x_k\|_1$ in (16). It should also be noted that the duration of e_k would have no effect on (16). In other words, the proposed robust RLS algorithm will exhibit robust performance with respect to a long burst of impulsive noise using the well known vector-norm inequality

$$\frac{1}{\sqrt{M}} \|\Delta w_k\|_1 \le \|\Delta w_k\|_2 \le \|\Delta w_k\|_1 \tag{17}$$

And (16), we note that the L_2 norm of the differential-coefficient vector would also remain bounded and hence the L_2 norm of w_k in the proposed RLS algorithm would also be robust with respect to the amplitude and duration of the impulsive-noise corrupted e_k .

III. COMPUTATIONAL COMPLEXITY

For stationary environments, the proposed algorithm entails $3M^2+4M+5$ multiplications and M^2+2M+2 additions per iteration where is the dimension of the coefficient vector. On the other hand, the conventional RLS algorithm requires $3M^2+4M+2$ multiplications and $2M^2+2M$ additions. Evidently, for values of in excess of 5, the computational complexity of the proposed robust RLS algorithm is similar to that of the RLS algorithms.

ROBUST RLS ALGORITHM

Table 1: Implementation of Proposed Robust RLS Algorithm for Stationary Environment

$Given\, dk\, and\, x_k,\, Choose\, P, \lambda_f, S_0 = \varepsilon^{-1} I, and\, compute$

$$e_k = d_k - w^T{}_{k-1} x_k$$

$$t_k = S_{k-1} x_k$$

$$\tau_k = x_k{}^T t_k$$

$$\tilde{\tau}_k = \frac{\lambda_k}{\delta_k} + \tau_k$$

$$\tilde{t}_k = \frac{1}{\tilde{\tau}_k} t_k$$

$$S_k = \frac{1}{\lambda_k} (S_{k-1} - \tilde{t}_k t_k{}^T)$$

$$w_k = w_{k-1} + e_k \tilde{t}_k$$

$For\, applications\, in\, stationary\, environments, compute$

$$\lambda_k = \lambda_f$$

$$\|x_k\|_1 = \|x_{k-1}\|_1 + |x_k| - |x_{k-M}|$$

$$\delta_k = \min(1, \frac{1}{\|x_k\|_1 |e_k|})$$

IV. SIMULATION RESULTS

The proposed robust RLS (PRRLS) algorithm is compared with the conventional RLS algorithm and the conventional LMS algorithm [4] in terms of robustness and noise cancellation application in stationary environments. Here input is a cosine wave in which random noise is added previously and then it will pass through adaptive filters where weights are updated as per algorithms. For RRLS regularization parameter is also updated as per above mention algorithm with the help of weights of adaptive filter. Simulation framework is done in MATLAB 7.0.1. The comparative results of all three algorithms are displayed in fig.2. The above figure shows the reduction in error is much higher when regularization parameter is continuously updated with error and in this manner our results are obtained with less amount of error.

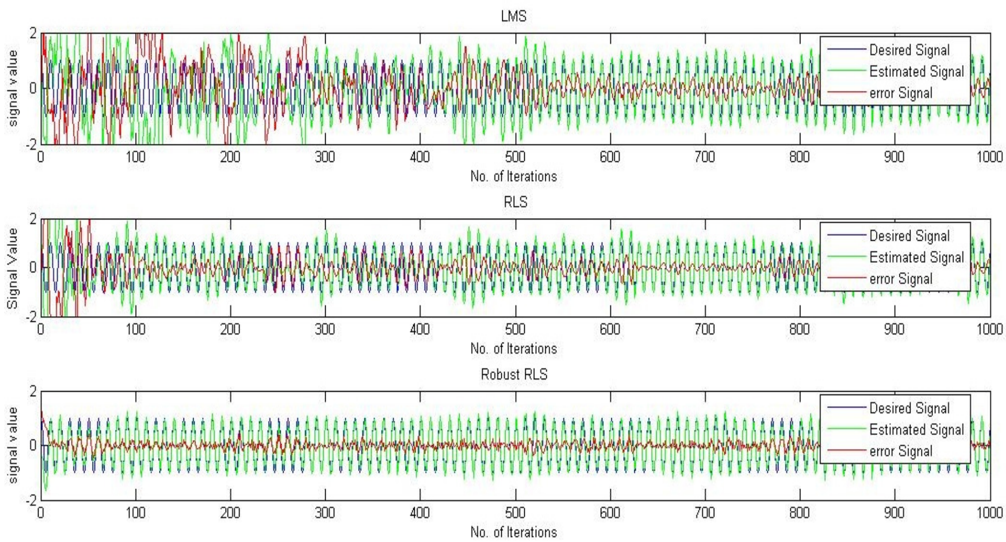

Fig.2: Simulation Results for LMS, RLS, RRLS with μ= 0.005, λ = 0.99.

V. CONCLUSION & FUTURE WORK

A new robust RLS adaptive-filtering algorithm that performs well in acoustic noise environments has been proposed. The New algorithm uses the norm of the gain factor of the cross-correlation vector to achieve robust performance against acoustic noise. In addition, the proposed algorithm uses a modified variance estimator to compute a threshold that is used to obtain A variable Regularization Parameter which offers improved tracking. Simulation results show that the proposed algorithm is robust against noise and offers better tracking compared to the conventional RLS and LMS algorithms.

For the linearly-constrained adaptive filters considered in the report, the set of equations specifying the constraints was assumed to be fixed and perfectly known throughout the 168 adaptation. In some applications this may not hold true for all time instants. For example, we may have a mismatch in the vectors building the constraint matrix as compared to the true ones, or the constraint values and the constraint matrix could be time-varying.

The case of constraint mismatch can cause signal cancellation of the signal of interest. Algorithms more robust to mismatch in the constraint matrix could be obtained if quadratic constraints are incorporated into the solution. This should be investigated for the proposed linearly-constrained adaptive filtering algorithms. If constraint values are time-varying, convergence problems may occur because the optimal solution will change accordingly.

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