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Robustness for IIR Filter by Means Regularization Parameter

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Abstract—***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 convergence rate, absolute error for an IIR Filter.***

Keywords- ***Adaptive Algorithm: RLS, RRLS Algorithm, Regularizing parameter.***

I. INTRODUCTION

Over years, however, numerous (mostly heuristic) variations of the LMS & RLS algorithm have been developed to overcome practical implementation problems (see [l] and [4] for instance). The contamination of the reference signal (see Figure 1) with the output of the adaptive filter has proven to further complicate the implementation problems. Thus systematic approaches for the design and analysis of the adaptive filters for realistic control scenarios have been of primary interest to researchers in the field. In [3], an estimation-based approach to the design of adaptive IIR filters is proposed. **T**HE convergence performance of adaptive filters depends critically on the randomness of the input-desired signal pairs [1]. Impulsive disturbances or noise in the input-desired signal pairs can cause the performance of adaptive filters to deteriorate [2]. Robustness in adaptive filters in impulsive-noise environments is achieved in a number of ways [2]. In [3]–[5], adaptive-filter robustness is considered as insensitivity to impulsive noise and in [6] it is deemed to be the capability of an adaptive filter to re-converge to the steady-state solution at the same rate of convergence as before. The robust algorithms in [3], [4] use the Hampel three-part re descending M-estimate objective function and that in [5] uses the Huber two-part M-estimate objective function. In [3]–[5], the median absolute deviation (MAD) [7] is used to estimate the variance of the error signal in order to determine appropriate threshold values. The amplitude of the error signal is then compared with these thresholds values to detect the presence of impulsive noise and whenever such noise is present, the algorithm either reduces the learning rate significantly or discards the error signal completely in the coefficient vector update equation. In [6], the instantaneous power of the weighted error signal is lowpass filtered and then used to switch the step size of the algorithm between two levels one of which suppresses the error signal corrupted by impulsive noise during the adaptation of the coefficient vector. The robust algorithms in [4]–[6] belong to the recursive least-squares (RLS) family and hence they converge significantly faster than algorithms of the steepest-descent family [1]. Reference [3] uses an adaptive ANC scenario to explain how an estimation interpretation of the adaptive control problem provides a framework for the systematic synthesis and analysis of adaptive FIR filters. This paper extends the results in [3] to the design of adaptive Infinite Impulse Response (IIR) filters. The formulation presented here also applies when the reference signal is contaminated with a feedback from the output of the adaptive filter (Figure 1).
The former uses a random-walk model for the variations in the optimal weight vector, while the latter assumes deterministic variations in the optimal weight vector. The steady-state performance of this algorithm in the non stationary environment for the white input is presented in [6]. The tracking performance analysis of the signed regressor LMS algorithm can be found in [7], [8], [9]. Also, the steady-state and tracking analysis of this algorithm without the explicit use of the independence assumptions are presented in [10]. Obviously, a more general analysis encompassing as many different algorithms as possible as special cases, while at the same time making as few restrictive assumptions as possible, is highly desirable. In [11], a unified approach for steady state and tracking analysis of LMS, NLMS, and some adaptive filters with the nonlinearity property in the error is presented.

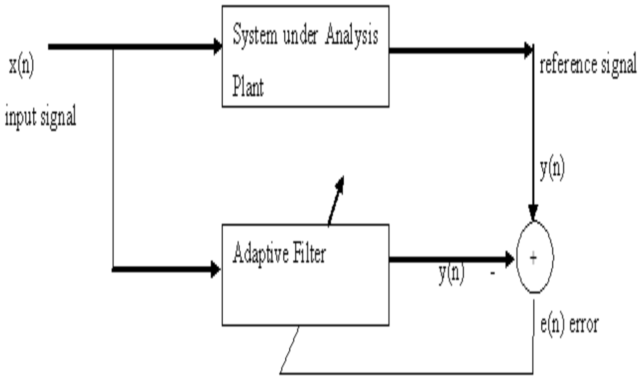


Fig.1: Basic design of a system Identification

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

We discuss the estimation-based approach to the design of an adaptive IIR filter , weighted least-squares algorithms obtain the optimal coefficient vector at iteration by solving the optimization problem $min_w \sum_{i=1}^{k} q_i (d_i - W_k{}^T x_i)^2$ (1) Where is the desired signal, is the input signal vector, and is a nonnegative weight at iteration. Each of vectors and is of dimension. 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 to zero. The input-signal autocorrelation matrix, and cross correlation vector, at iteration are given by

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

$$P_k = \lambda_f P_{k-1} + \delta_k x_k d_k \qquad (3)$$

Where R_k and P_k are of dimensions [M,M] and m , respectively, and 0<<λ_f <1. Parameter λ_f is a prespecified fixed forgetting factor and δ_k is a nonnegative scalar. The normal equations of (1) can be expressed in matrix form as

$$w_k = R_k^{-1} P_k \qquad (4)$$

Using the matrix inversion lemma [1], [2] in (2), we obtain the update equation of the inverse of the autocorrelation matrix as

$$R_k^{-1} = \lambda^{-1} R_{k-1}^{-1} - \frac{\lambda^{-2} R_{k-1}^{-1} x_k x_k^T R_{k-1}^{-1}}{\frac{1}{\delta_k} + \lambda^{-1} x_k^T R_{k-1}^{-1} x_k} \qquad (5)$$

Now using (5) in (4), the update equation of the coefficient

$$W_k = W_{k-1} + K_k e_k \text{ Where } K_k = \frac{\lambda^{-1} R_{k-1}^{-1} x_k}{1+\lambda^{-1} x_k^T R_{k-1}^{-1} x_k} \qquad (6)$$

and $e_k = (d_k - x_k W_{k-1})$ (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

$$\left\| P_k - \lambda_f P_{k-1} \right\|_1 = \| \delta_k x_k d_k \|_1 \qquad (8)$$

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

$\left\|P_k - \lambda_f P_{k-1}\right\|_1 \leq \gamma_k$ (9)

Parameter is chosen as

$\gamma_k = \frac{d_k}{e_k}$ (10)

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

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

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

With $\delta_k = 1$, 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., $R_k^{-1} - \lambda^{-1} R_{k-1}^{-1}$, given by

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

As can be seen, for an impulsive-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 $\delta_k = \frac{1}{\|x_k e_k\|_1}$ 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 $\|x_k\|_\infty / e_k$ respectively. As a result, the norm of the13) 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} (14)

is obtained as $\|\Delta W_k\|_1 = \frac{|e_k| \|R_{k-1}^{-1} \ x_k\|_1}{\|1+\lambda^{-1} x_k^T R_{k-1}^{-1} \ x_k\|_1}$ (15)

by using (6) in (14) with $\delta_k = 1$. As can be seen, the L1norm of the differential-coefficient vector in the conventional RLS algorithm increases abruptly for an impulsive noise corrupted . Similarly, the L1norm 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

$\|\Delta W_k\|_1 = \frac{\|R_{k-1}^{-1} \ x_k\|_1}{\|x_k\|_1 \|\lambda \ \ + x_k^T R_{k-1}^{-1} \ x_k\|_1}$ (16)

As can be seen, the L1 norm given by (16) would be much less than that in (15) since e_k cannot perturb ${R_{k-1}}^{-1}$. 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 would exhibit robust performance with respect to a long burst of impulsive noise. Using the well known vector-norm inequality $\frac{1}{\sqrt{M}} \|\Delta W_k\|_1 \leq \|\Delta W_k\|_2 \leq \|\Delta W_k\|_1$ (17)

and (16), we note that the L2 norm of the differential-coefficient vector would also remain bounded and hence the L2 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.

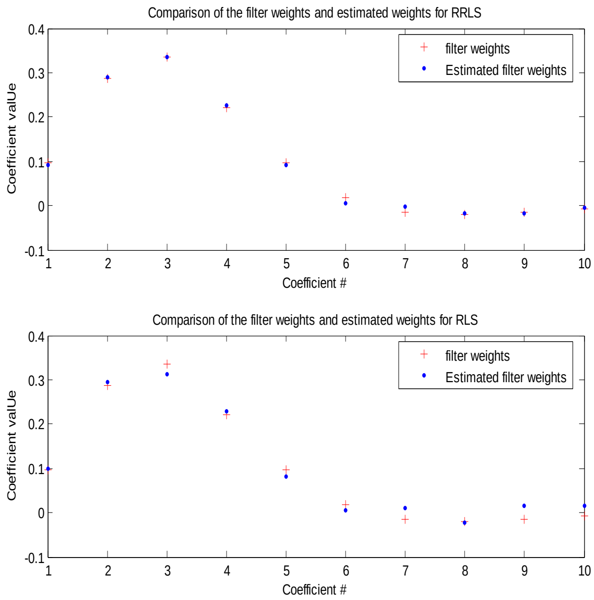
RRLS Algorithm

Let $R^{-1}{}_0 = \delta^{-1} I,\ where\ \delta\ is\ small\ positive\ constant$
For each k
{
$K_k = R_k^{-1} x_k$
$K_k = \dfrac{\lambda^{-1} R_{k-1}^{-1}\ x_k}{\frac{1}{\delta_k} + \lambda^{-1} x_k^T R_{k-1}^{-1}\ x_k}$
$R_k^{-1} = \lambda^{-1} R_{k-1}^{-1} - \lambda^{-1} K_k X_k^T R_{k-1}^{-1}$
$e_k = d_k - x_k W_{k-1}$
$W_k = W_{k-1} + R_k^{-1} x_k\ e_k$
$\|x_k\|_1 = \|x_{k-1}\|_1 + \|x_k\| - \|x_{k-M}\|$
$\delta_k = min\left(1, \dfrac{1}{\|x_k\|_1 \|e_k\|}\right)$
}

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

IV. SIMULATION RESULTS:

The experimental results for IIR filter using RLS is mentioned below in the impulse responses of the filters were modeled, for practical reasons, a low-pass digital Butterworth IIR filter with order of n=2 with normalized cutoff frequency W_n=0.25 is used. Noise source is a zero-mean Gaussian process with variance 1, and it is assumed to be dependent on filter weight it is added to output of filter to receive desired signal. The Monte Carlo simulations resulting of running of RLS for forgetting factor =0.99 for 2000 trials, are shown in Fig 3.6. Here fig. 3.6(a) gives the response of all three (desired, estimated, error signals) signals response while fig. 3.6(b) gives the tracking of algorithm's weight to the original IIR filter weight which is very close to originals weights, while last one is showing the convergence.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 results of all 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.



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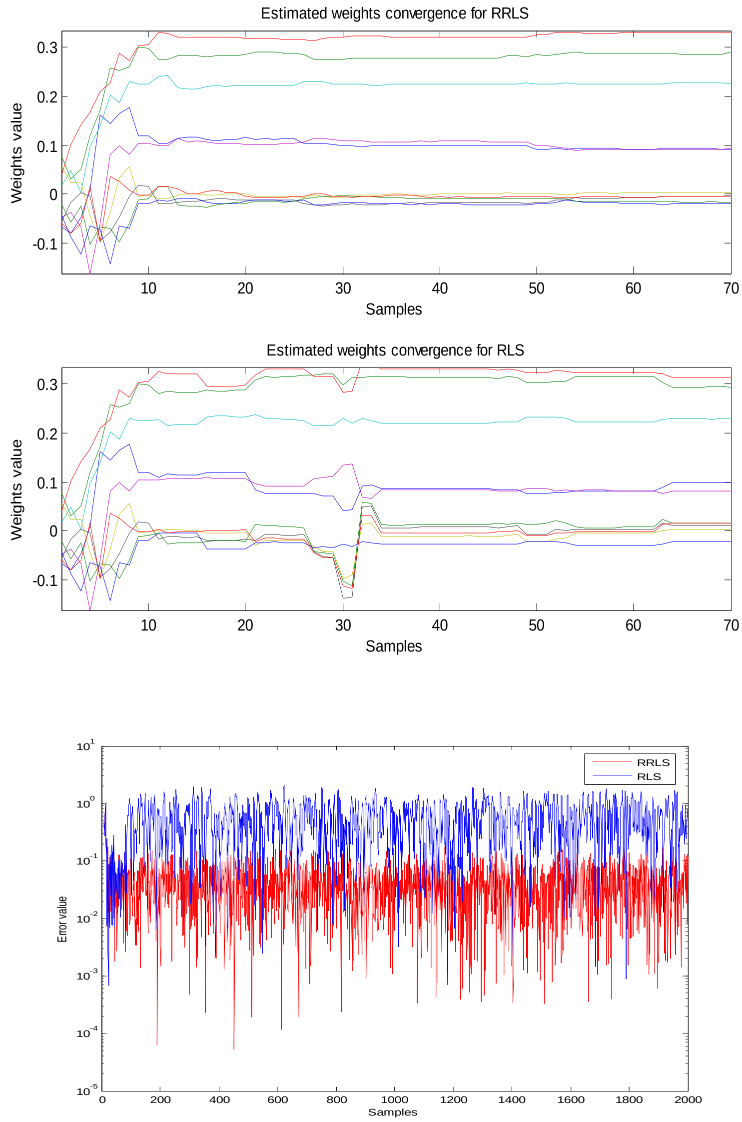

Fig 2 : Results from Conventional RLS and RRLS for IIR Filter where λ=0.99 for N=2000 iterations (a)comparison of the filter weight & actual weights, (b) Estimated weight convergence, (c) Absolute error using RLS, RRLS Algorithm

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 as can be seen, the RLS algorithms cannot track sudden system changes whereas the PRRLS algorithm handles sudden system changes successfully and at the same time maintains its robustness with respect to impulsive noise.. 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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