STUDY OF FILTERED-X LOGARITHMIC RECURSIVE LEAST P-POWER ALGORITHM

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ABSTRACT

For active impulsive noise control, a filtered-x recursive least p-power (FxRLP) algorithm is proposed by minimizing the weighted summation of the p-power of the a posteriori errors. Since the characteristic of the target noise is investigated, the FxRLP algorithm achieves good performance and robustness. To obtain a better performance, we develop a filtered-x logarithmic recursive least p-power (FxlogRLP) algorithm which integrates the p-order moment with the logarithmic-order moment. Simulation results demonstrate that the FxlogRLP algorithm is superior to the existing algorithms in terms of convergence rate and noise reduction.

Index Terms— Active impulsive noise control, filtered-x recursive least p-power (FxRLP), filtered-x logarithmic recursive least p-power (FxlogRLP), impulsive noise.

1. INTRODUCTION

On the basis of wave-superposition principle, active noise control (ANC) is realized by utilizing adaptive filters to generate a signal with same magnitude but opposite phase of the signal to be canceled. Thanks to the low computational complexity and simple structure, the filtered-x least mean square (FxLMS) algorithm is frequently performed in the adaptive filtering algorithms [7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80]. As compared to the FxLMS algorithm, the filtered-x recursive least square (FxRLS) algorithm [80] can provide faster convergence rate at the cost of higher computational complexity.

Note that the FxRLS algorithm is based on the assumption that the reference signal follows the Gaussian distribution. But in fact, the target noise always contains outliers, that is, the impulsive noise. For such situations, the FxRLS algorithm always shows bad performance and has stability problems. To address this problem, instead of the mean-square error (MSE) used in the FxLMS algorithm, the filtered-x least mean p-power (FxLMP) algorithm was proposed [85] by minimizing the mean p-power of error. In [86], the filtered-x logarithmic least mean square (FxlogLMS) algorithm was proposed by minimizing the squared logarithmic transformation of the error signal. Simulation results demonstrated that the FxlogLMS algorithm has good robustness and better performance. Furthermore, to achieve faster convergence rate, the filtered-x logarithmic recursive least squares (FxlogRLS) algorithm was proposed [87] by minimizing the weighted summation of the logarithmic transformation of the a posteriori errors.

In this work, we try to work out the above problem in another way. To investigate the characteristic of the target noise, a filtered-x recursive least p-power (FxRLP) algorithm is proposed by minimizing the weighted summation of the p-power of the a posteriori errors. Then, by integrating the p-order moment with the logarithmic-order moment, we develop a filtered-x logarithmic recursive least p-power (FxlogRLP) algorithm.

The main contributions of this paper are summarized as follows: 1) By defining a new cost function based on the p-power of error, a new adaptive filtering algorithm is proposed, which is an extension of the FxLMP algorithm in the recursive least squares structure. 2) By integrating the p-order moment with the logarithmic-order moment, a novel adaptive filtering algorithm is developed. It is worth noting that this paper for the first time combines the benefits of the FxLMP-type algorithm and the FxlogLMS-type algorithm. 3) The properties of the proposed algorithms and their relationship to the existing algorithms are illustrated in detail.

The rest of this paper is organized as follows. Section 2 presents the derivation of the proposed FxRLP algorithm, and the proposed FxlogRLP algorithm is derived in Section 3. In Section 4, the mean stabilities of the proposed algorithms are analyzed. Section 5 illustrates the simulation results, and the conclusions are drawn in Section 6.

2. FXRLP ALGORITHM

Fig. 1 shows a single-channel feed-forward ANC system, where $P(z)$ represents the primary path between the reference signal $x(n)$ and the error microphone $e(n)$, $d(n)$ is the primary noise, $S(z)$
denotes the secondary path from the adaptive filter \( W(z) \) to the error microphone \( e(n) \), \( \hat{S}(z) \) can be obtained by using an off-line or on-line system identification approach \([88, 89, 90]\), and \( y(n) \) represents the output of the secondary sound source. Then, the error microphone \( e(n) \) can be calculated by

\[
e(n) = d(n) - y(n) = d(n) - s(n) * [w^T(n)x(n)],
\]

where \( x(n) = [x(n), x(n-1), ..., x(n-L+1)]^T \) represents the reference signal vector, \( s(n) \) denotes the transposition.

Remark 1: Since the impulsive noise can be modeled as a \( \alpha \)-stable process \( 0 < \alpha < 2 \), \( \alpha \) is the characteristic exponent, the second-order moment of the impulsive noise is not finite and the adaptive algorithm based on the MSE suffers from the stability problem. Hence, it is wise to use the cost function with the fractional lower order moment (\( p \)-power of error, \( 1 < p < \alpha \)) for designing the robust adaptive algorithm.

Here, the cost function of the FxRLP algorithm is defined as

\[
J_{FxRLP}(n) = \sum_{i=1}^{n} \lambda^{n-i} |\varepsilon(i, n)|^p
\]

where \( 0 < \lambda < 1 \) denotes the forgetting factor, \( \varepsilon(i, n) = d(i) - w^T(n)x_s(i) \) represents the a posteriori error, \( w(n) \) is the adaptive filter tap weight vector with length \( L \), \( x_s(n) = [x_s(n), x_s(n-1), ..., x_s(n-L+1)]^T \), \( x_s(n) = \tilde{s}(n) * x(n) \), and \( \tilde{s}(n) \) denotes the impulse response of \( \hat{S}(z) \).

Taking the gradient of \( J_{FxRLP}(n) \) with respect to \( w(n) \) and equating the result to zero, one gets

\[
\frac{\partial J_{FxRLP}(n)}{\partial w(n)} = -p \sum_{i=1}^{n} \lambda^{n-i} |\varepsilon(i, n)|^p \frac{\varepsilon(i, n)}{|\varepsilon(i, n)|} x_s(i) = 0
\]

which can be written as

\[
\sum_{i=1}^{n} \lambda^{n-i} v(i, n) x_s(i)x_s^T(i) w(n) = \sum_{i=1}^{n} \lambda^{n-i} v(i, n) x_s(i)d(i)
\]

where \( v(i, n) = \frac{|\varepsilon(i, n)|^p}{|\varepsilon(i, n)|} \).

From [4], we obtain the following expression for \( w(n) \)

\[
w(n) = P(n) \theta(n)
\]

where

\[
P(n) = R^{-1}(n),
\]

\[
R(n) = \sum_{i=1}^{n} \lambda^{n-i} v(i, n) x_s(i)x_s^T(i),
\]

and

\[
\theta(n) = \sum_{i=1}^{n} \lambda^{n-i} v(i, n) x_s(i)d(i).
\]

To derive an on-line algorithm, the following approximations are used:

\[
R(n) \approx \sum_{i=1}^{n} \lambda^{n-i} v(i, i)x_s(i)x_s^T(i) = \lambda R(n-1) + v(n, n)x_s(n)x_s^T(n),
\]

\[
\theta(n) \approx \sum_{i=1}^{n} \lambda^{n-i} v(i, i)x_s(i)d(i) = \lambda \theta(n-1) + v(n, n)x_s(n)d(n).
\]

By using Woodbury’s matrix inversion lemma \([91, 92, 93]\), the inverse autocorrelation matrix can be updated by

\[
P(n) = \lambda^{-1} P(n-1) - \lambda^{-1} K(n)x_s^T(n)P(n-1)
\]

where the gain vector is defined as

\[
K(n) = \frac{v(n, n)P(n-1)x_s(n)}{\lambda + v(n, n)x_s^T(n)P(n-1)x_s(n)}.
\]

According to (11), (12) can be simplified as

\[
K(n) = v(n, n)P(n)x_s(n).
\]

From [5], [10], [11] and [13], \( w(n) \) can be updated by

\[
w(n) = P(n)(\lambda \theta(n-1) + v(n, n)x_s(n)d(n)) = \lambda P(n) \theta(n-1) + v(n, n)P(n)x_s(n)d(n)
\]

\[
= P(n-1) \theta(n-1) - K(n)x_s^T(n)P(n-1) \theta(n-1) + K(n)d(n)
\]

\[
= w(n-1) + K(n) \phi(n)
\]

where \( \phi(n) = d(n) - x_s^T(n)w(n-1) \) is the a priori error.

3. FXLOGRLP ALGORITHM

According to the zero-order statistics \([94]\) which states that the \( \alpha \)-stable process is a logarithmic-order process with finite logarithmic moments, we define a new cost function as follows

\[
J_{FxLogRLP}(n) = \sum_{i=1}^{n} \lambda^{n-i} \log^p(1 + |\varepsilon(i, n)|).
\]

Taking the gradient of \( J_{FxLogRLP}(n) \) with respect to \( w(n) \) and letting the result to zero, we obtain

\[
\frac{\partial J_{FxLogRLP}(n)}{\partial w(n)} = -p \sum_{i=1}^{n} \lambda^{n-i} \frac{\log^p(1 + |\varepsilon(i, n)|)}{(1 + |\varepsilon(i, n)|)} |\varepsilon(i, n)| x_s(i) = 0
\]
which can be rewritten as
\[
\sum_{i=1}^{n} \lambda^{n-i} v(i, n) x(i) x^T(i) w(n) = \sum_{i=1}^{n} \lambda^{n-i} v(i, n) x(i) d(i)
\]
where \( v(i, n) = \frac{\log^{-1}(1+c(n))}{(1+c(n))} \).

The following derivation of the FxlogRLP algorithm is the same as that of the FxRLP algorithm, as shown in [8]–[11].

Remark 2: To implement the FxRLP and FxlogRLP algorithms recursively and efficiently, we replace the \( \text{a priori} \) error \( \varepsilon(n) \) and the \( \text{a posteriori} \) error \( \varepsilon(n) \) by the residual noise \( e(n) \) which can be measured by the error sensor. Here, \( e(n) \) and \( v(n) \) represent \( e(n, n) \) and \( v(n, n) \), respectively. Table I summarizes the proposed algorithms, where \( \delta \) is a small positive value, \( I \) is the identity matrix and \( \tau \) is a small positive constant to avoid division by zero.

### Table 1. Summary of the proposed algorithms

| Initialization: |
|------------------|
| \( w(0) = 0 \), \( P(0) = \delta I \) |

| Parameters: |
|--------------|
| \( \tau, \lambda, p \) |

| Update: |
|---------|
| for \( n = 1, 2, 3, \ldots \) |
| \( v(n) = \frac{\log^{-1}(1+c(n))}{(1+c(n))} \) (FxRLP) |
| \( v(n) = \frac{\log^{-1}(1+c(n))}{(1+c(n))} + \frac{\lambda}{\tau} \) (FxlogRLP) |
| \( K(n) = \frac{v(n) P(n-1) x_s(n)}{\lambda + v(n) x_s^T(n) P(n-1) x_s(n)} \) |
| \( w(n) = w(n-1) + K(n) c(n) \) |
| \( P(n) = \lambda^{-1} P(n-1) - \lambda^{-1} K(n) x_s^T(n) P(n-1) \) |

Remark 3: As can be seen from Table I the FxRLP and FxlogRLP algorithms have the same structure except for the calculation of \( v(n) \). Note that the FxRLP algorithm reduces to the FxLSL algorithm when \( v(n) = 1 \) (i.e., \( p = 2, \tau = 0 \)).

### 4. MEAN STABILITY ANALYSIS

In this section, we perform the mean stability analyses of the proposed algorithms.

According to Table I the weight vector can be summarized and rewritten as follows
\[
w(n+1) = w(n) + \frac{v(n) P(n-1) x_s(n)}{\lambda + v(n) x_s^T(n) P(n-1) x_s(n)} e(n).
\]

Define the weight deviation vector below
\[
\tilde{w}(n) = w_o - w(n)
\]
where \( w_o \) denotes the optimal weight vector of the controller. Subtracting (18) from \( w_o \), we have
\[
\tilde{w}(n+1) = \tilde{w}(n) - \frac{v(n) P(n-1) x_s(n)}{\lambda + v(n) x_s^T(n) P(n-1) x_s(n)} e(n).
\]

Taking the expectation on both sides of (20) yields
\[
E[\tilde{w}(n+1)] = E[\tilde{w}(n)] - \frac{v(n) P(n-1) x_s(n)}{\lambda + v(n) x_s^T(n) P(n-1) x_s(n)} E[e(n)]
\]
which can be expressed as
\[
E[\tilde{w}(n+1)] = E[\tilde{w}(n)] - \frac{v(n) P(n-1) x_s(n) x_s^T(n)}{\lambda + v(n) x_s^T(n) P(n-1) x_s(n)} \tilde{w}(n)
\]
\[
\approx E[\tilde{w}(n)] - \frac{v(n) P(n-1) x_s(n) x_s^T(n)}{\lambda + v(n) x_s^T(n) P(n-1) x_s(n)} E[\tilde{w}(n)]
\]
where \( E[\cdot] \) represents the expectation operator, and the approximation \( x_s^T(n) \tilde{w}(n) \) was used.

Therefore, the algorithm converges in the mean if and only if
\[
0 < \lambda_{\max} \left\{ E \left[ \frac{v(n) P(n-1) x_s(n) x_s^T(n)}{\lambda + v(n) x_s^T(n) P(n-1) x_s(n)} \right] \right\} < 2
\]
where \( \lambda_{\max} \{ \cdot \} \) denotes the largest eigenvalue of the matrix.

Remark 4: Based on the fact that \( \lambda_{\max}(AB) < \text{Tr}(AB) \) in (23), it obtains
\[
\lambda_{\max} \left\{ E \left[ \frac{v(n) P(n-1) x_s(n) x_s^T(n)}{\lambda + v(n) x_s^T(n) P(n-1) x_s(n)} \right] \right\} < E \left[ \frac{\text{Tr}(x_s^T(n) P(n-1) x_s(n))}{v(n) + x_s^T(n) P(n-1) x_s(n)} \right] < 1.
\]

Hence, the proposed algorithms are convergent in the mean if the input signal is persistently exciting.

### 5. SIMULATION RESULTS

Simulations are carried out to examine the performance of the proposed algorithms for active impulsive noise control. The primary path \( P(z) \) and secondary path \( S(z) \) are modeled as finite impulse response (FIR) filters with the length of 256 and 100, respectively, and the estimated secondary path \( \hat{S}(z) \) was exactly identified as \( S(z) \). The magnitude and phase responses of the primary and secondary paths are shown in Fig. 2. The adaptive filter \( W(z) \) is selected as an FIR filter with the length of 128. The reference signal \( x(n) \) is generated through a standard symmetric \( \alpha \)-stable (\( \alpha \)-S\( \alpha \)) process with \( \alpha = 1.35 \) or \( \alpha = 1.55 \) [87].

To evaluate the performance of the algorithms, the averaged noise reduction (ANR) is used:
\[
ANR(n) = 20 \log \left( A_c(n)/A_d(n) \right),
\]
where
\[
A_c(n) = \xi A_c(n-1) + (1 - \xi)|e(n)|,
\]
\[
A_d(n) = \xi A_d(n-1) + (1 - \xi)|d(n)|,
\]
and \( \xi = 0.999 \). The simulation results are obtained by ensemble averaging over 50 trials.

In the following simulations, the proposed algorithms are compared with the FxLMP [65], FxRLS [60], and FxlogRLS [87] algorithms, and the parameters are set as follows: the step size is \( \mu = 0.0001 \) for the FxLMP algorithm; the forgetting factor \( \lambda = 0.999 \)
and $\delta = 0.001$ are set for the $\text{FxRLS}$, $\text{FxlogRLS}$, $\text{FxRLP}$ and $\text{FxlogRLP}$ algorithms; $p = 1.3$ (1.5) is set for the $\text{FxLMP}$, $\text{FxRLP}$ and $\text{FxlogRLP}$ algorithms under the $\text{S\&S}$ signal with $\alpha = 1.35$ (1.55); $\tau = 0.001$ is set for the $\text{FxRLP}$ and $\text{FxlogRLP}$ algorithms. The performance comparison of the algorithms is shown in Fig. 3. As can be seen, the $\text{FxRLS}$ algorithm diverges because the second-order moment of the target noise is not finite. The $\text{FxRLP}$ algorithm shows faster convergence speed relative to the $\text{FxLMP}$ algorithm, but has a higher steady-state ANR as compared to the $\text{FxlogRLS}$ algorithm. Owing to the new cost function which integrates the $p$-order moment with the logarithmic-order moment, the $\text{FxlogRLP}$ algorithm presents the best performance among the others.

6. CONCLUSION

By minimizing the weighted summation of the $p$-power of the $a$ posteriori errors, we proposed a $\text{FxRLP}$ algorithm for active impulsive noise control. Moreover, by integrating the $p$-order moment with the logarithmic-order moment, a $\text{FxlogRLP}$ algorithm was developed. Simulation results confirmed that the $\text{FxlogRLP}$ algorithm outperforms the state-of-the-art algorithms.

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