Kurtosis Driven Variable Step-Size Normalized Least Mean Square Algorithm for RF Repeater

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***Abstract*— This paper presents a new Kurtosis driven Variable Step-Size Normalized Least Mean Square (KVSS-NLMS) algorithm to prevent repeater from oscillation due to feedback signal of radio frequency (RF) repeater. To get better Mean Square Error (MSE) performance, step-size is adjusted using the kurtosis. The proposed algorithm shows the better performance of steady state MSE. The proposed algorithm shows a better ERLE performance than that of KVSS-LMS, VSS-NLMS, NLMS algorithms.**

***Index Terms*— KVSS-NLMS algorithm, Radio Frequency (RF) repeater, Oscillation.**

I. INTRODUCTION

Recently, as the mobile communication service is widely used and the demand for wireless repeaters is rapidly increasing because of the easiness of extending service areas. But the repeater has the interference due to the feedback signals between the transmit and receive antennas [1,2]. The Interference Cancellation System (ICS) prevents repeater from the oscillation by cancelling interference which are caused by the feedback signal of the repeater. The feedback signal from the output of the transmit antenna in a conventional Radio Frequency (RF) repeater causes the performance of the wireless communication systems to be degraded. Therefore the ICS is proposed which can prevent repeater from the oscillation by cancelling the interference feedback signal and improves the quality of signal by using Digital Signal Processing (DSP).

In this paper, we propose a new Kurtosis driven Variable Step Size Normalized Least Mean Square (KVSS-NLMS) algorithm, which utilizes kurtosis to adjust the step sizes, for canceling the feedback interference signals in the repeater for Wideband Code Division Multiple Access (WCDMA, 1920 – 2170 MHz) bands. Its target is to decrease Mean Square Error (MSE) and obtaining a good echo return loss enhancement (ERLE)[3]. The proposed algorithm can obtain better performance compared to NLMS, VSS-NLMS, Kurtosis driven VSS-LMS algorithms. The proposed algorithm shows a better ERLE performance with increased iterations.

This paper is organized as follows. In chapter 2, we describe VSS-LMS algorithm, and in chapter 3, we describe the proposed KVSS-NLMS algorithm. In chapter 4, we show simulation results that compares the proposed algorithm with others in view point of MSE and ERLE. Finally, conclusion follows in chapter 5.

II. VARIABLE STEP-SIZE LMS ALGORITHM

We consider the following system output error, step size.

$$e(n) = d(n) - y(n) = d(n) - w(n)x(n) \qquad (1)$$

$$\mu'(n+1) = \alpha\mu(n) + \gamma^2(n) \qquad (2)$$

with $0 < \alpha < 1, \gamma > 0$

Where, $e(n)$ is output error, $d(n)$ is desired signal, $y(n)$ is n-th output of a finite impulse response, $w(n)$ is weight vector, $x(n)$ is the input signal and $\mu(n)$ is step size parameter, $r(n)$ is additive noise.

and

$$\begin{aligned} \mu(n+1) &= \mu_{\max}(n), \ \ if \ \ \mu'(n+1) > \mu_{\max}(n) \\ &= \mu_{\min}(n), \ \ if \ \ \mu'(n+1) < \mu_{\min}(n) \\ &= \mu'(n+1), \ \ otherwise \end{aligned} \qquad (3)$$

Where $0 < \mu_{\min}(n) < \mu_{\max}(n)$. The initial step size $\mu_0(n)$ is usually taken to be $\mu_{\max}(n)$, the step size is $\mu(n)$ parameters α and γ. A typical value of α=0.97, and the parameter γ is usually small. Here $\mu_{\min}(n)$ is set to assure that the algorithm remains stable[3,4]. This is known as Variable Step-Size Least Mean Square (VSS-LMS) algorithm

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III. PROPOSED ALGORITHM

We propose a KVSS-NLMS algorithm. The NLMS algorithm is a modified version of LMS recursion algorithm. In NLMS algorithm, the weight vector is updated as Eq.(4). And step size is given as Eq.(5). Where $w(n)$ is weight vector, $\mu(n)$ is step size, $e(n)$ is error signal, $x(n)$ is input signal.

$$w(n+1) = w(n) + 2\mu(n)e(n)x(n) \qquad (4)$$

$$\mu(n) = \frac{1}{2x^T(n)x(n)} = \frac{1}{2\|x(n)\|^2} \qquad (5)$$

The updated weight of NLMS is as Eq.(6), Eq.(7).

$$w(n+1) = w(n) + \frac{1}{x^T(n)x(n)}e(n)x(n) \qquad (6)$$

and

$$w(n+1) = w(n) + \frac{\mu'(n)}{\varepsilon(n) + x^T(n)x(n)}e(n)x(n) \qquad (7)$$

Where $\varepsilon(n)$ are constants, $w(n)$ is weight vector, $\mu(n)$, $\mu'(n)$ is step size parameter.

The desired signal and error signal as Eq.(8), Eq.(9)[3].

$$d(n) = x(n) + r(n) \qquad (8)$$

and

$$e(n) = d(n) - y(n) \qquad (9)$$

Where $y(n)$ is output signal of the filter, $x(n)$ is input signal and $r(n)$ is additive noise.

In kurtosis, a time-varying sequence is updated as Eq.(10).

$$\rho(n+1) = \rho(n) + \delta \operatorname{sgn} \cdot \left\{E\{e^4(n)\} - \rho(n)E^2\{e^2(n)\}\right\} \qquad (10)$$

Where $\rho(n)$ is a time-varying sequence, δ is constant. We can obtain Eq.(11) by using Eq.(10). Error kurtosis estimator has the form as in ref.[5].

$$C_4^e(n) = E\{e^4(n)\} - \rho(n)E^2\{e^2(n)\} \qquad (11)$$

Eq.(12) is step-size which is depended on the kurtosis of the error[7].

$$\mu(n) = \alpha\left|C_4^e(n)\right|, \quad 0. < \alpha < 2 \qquad (12)$$

Where $\mu(n)$ is the step-size sequence, α is a positive constant, and $|\cdot|$ denotes the absolute value.

The proposed algorithm is Eq.(13). The step-size of this algorithm is depended on the kurtosis of the error.

$$\mu(n) = \begin{cases} \mu_{NLMS}(n), n \le L \\ \dfrac{1}{\delta + x^T x}(1 - e^{-\alpha\left|c_4^e(n)\right|}), n > L \end{cases} \qquad (13)$$

Where L is length of adaptive filter [8-13].

The ERLE is as Eq.(14)

$$ERLE = 10\log_{10}\frac{y(n+1)}{e(n+1)} \qquad (14)$$

with

$$e(n+1) = \lambda \cdot e(n) + \varepsilon \cdot e^2(n) \qquad 15)$$

$$y(n+1) = \lambda \cdot y(n) + \varepsilon \cdot d^2(n) \qquad (16)$$

Where λ, ε is constant(λ = 0.997, ε = 0.00048), $e(n)$ is output error, $y(n)$ is output signal, $x(n)$ is input signal, $d(n)$ is desired signal.

IV. SIMULATIONS RESULTS

System identification setup is shown in Fig. 1.

Fig. 2 shows mean square error vs. iteration time between NLMS, VSS-NLMS, KVSS-LMS algorithm and proposed algorithm. The proposed algorithm has better MSE performance by 5dB to 25dB than KVSS-LMS, VSS-NLMS, NLMS algorithms.

Fig. 3 compares the mean square error vs. iteration number according to the alpha value of the proposed algorithm and other algorithm. Large alpha value results in better MSE performance.

Fig. 4 shows the ERLE vs. iteration number between the proposed and KVSS-LMS, VSS-NLMS, NLMS algorithms. From Fig. 4, the proposed algorithm shows a better ERLE performance than that of KVSS-LMS, VSS-NLMS, NLMS algorithms.

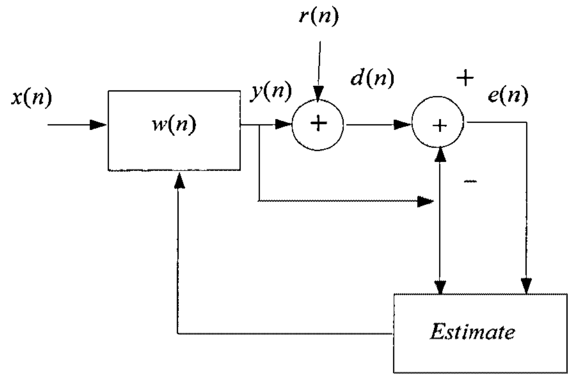

Fig. 1. System identification setup.

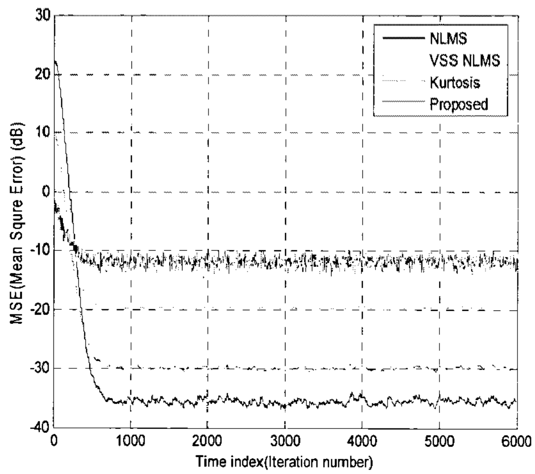

Fig. 2. Mean square error vs. iteration number between the proposed algorithm and other algorithms.

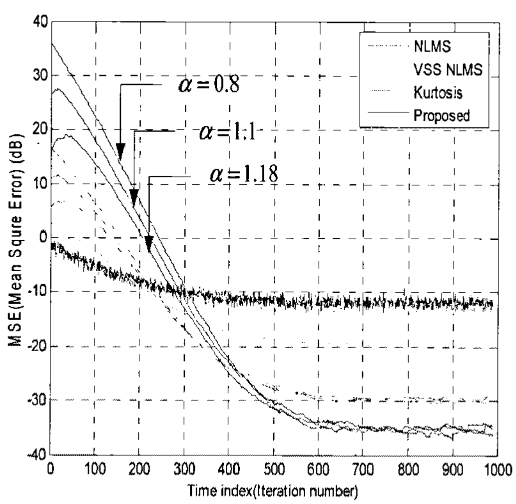

Fig. 3. Mean square error vs. iteration number of the proposed algorithm according to alpha and other algorithms.

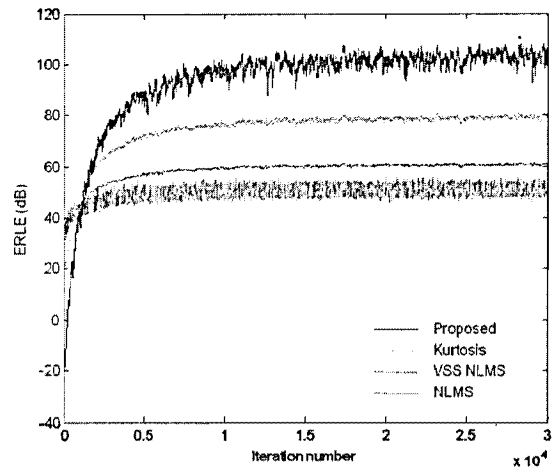

Fig. 4. Echo return loss enhancement vs. iteration number of the proposed algorithm and other algorithms.

V. CONCLUSIONS

The KVSS-NLMS adaptive algorithm is proposed. The simulation results show that the proposed KVSS-NLMS algorithm has a better MSE performance that that of other algorithms. The proposed algorithm has 5dB to 25dB better MSE performance compared to KVSS-LMS, VSS-NLMS, NLMS algorithms. The proposed algorithm shows a better ERLE performance with increased iterations.

The implementation of the proposed algorithm can be done in a standard Field Programmable Gate Array (FPGA) so that the system can be realized very efficiently.

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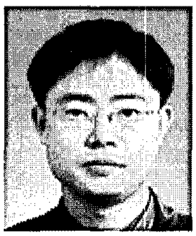

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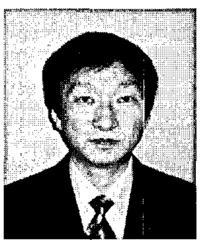

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