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INTERFERENCE SUPPRESSION TECHNIQUES

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Abstract: ***In this paper, comparison of classic adaptive-filtering algorithms, such as LMS and RLS of Volterra filter, consist of adapting the coefficients of linear filters in real time. These algorithms have applications in a number of situations where the signals measured in the environment can be well modeled as Gaussian noises applied to linear systems, and their combinations are of additive type and analysis the performance of the DSSS receiver containing the Volterra Jilter in the presence of the broadband BPSK interference is addressed. Recursive least square (RLS) is used in the filter adaptation process. Obtained results show that the Volterra filter receiver obtains the excellent interference suppression, compared to the receiver containing the two-sided transversal filter.***

Keywords: Volterra LMS algorithm, Volterra RLS algorithm,Volterra kernels and DSSS.

1. INTRODUCTION

In this paper, we will describe some of the techniques available to model nonlinear systems using nonlinear adaptive systems using the general structure depicted in Fig.1. In particular, the following approaches for nonlinear adaptive filtering will be discussed here:

- The non-recursive polynomial model based on the Volterra series expansion.
- The recursive polynomial model based on nonlinear difference equations.

we will introduce the methods above mentioned for modeling nonlinear systems and for each approach adaptive algorithms for updating the corresponding nonlinear filter coefficients will be described.

1.1. INTERFERENCE

Any signal is transmitted by transmitter, gets some attenuation over distance and finally received at receiver as distorted version of itself. The signal is decoded by treating the sum of all the other on-going signal transmissions as noise. Decoding success is a random event whose probability depends upon the desired signal strength, the level of thermal noise, and the strength of interfering signals. At the R&D phase, every system design aims at transmitting and receiving data or voice with some specified bit error-rate at optimum signal conditions, usually for a specified carrier-to-interference (C/I) ratio. But the design must also allow for marginal signal conditions and allow for signal fading, reflections, atmospheric effects, rain attenuation, multi-path fades, and interfering signals.

1.2. RECOGNIZING THE INTERFERENCE

The frequency of an interfering signal is the most common parameter leading to the identification of the interfering source. Thus, an interference problem can often be categorized by its frequency characteristics. It should be noted that whether the interfering signal is in-band or out-of-band, the signal is almost certainly coming through the antenna, down the cable, and into the affected receiver. Therefore, a spectrum analyzer connected to the operating system antenna will serve as a substitute measuring receiver which will display and help identify unwanted signals.

2. REMOVING INTERFERENCE USING NON LINEAR VOLTERRA FILTER

A nonlinear filter cannot be described by an impulse response. Nonlinear filters can be modeled by using polynomial models of non-linearity. Volterra series expansion can model a large class of nonlinear filters and systems. Algorithms driven by Volterra series: LMS Volterra Filter, RLS Volterra Filter.

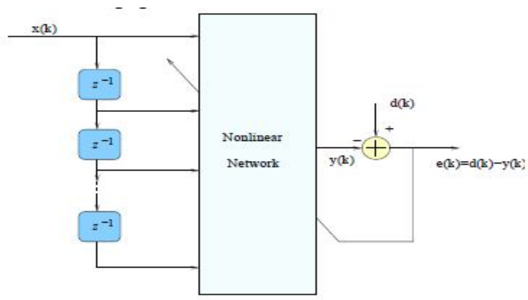


Fig.1 Adaptive nonlinear filter

Linear combination of nonlinear functions of the input signal , the input-output relationship can be expressed easily in a vector form.

$$y(k) = X^T(k)w \tag{1}$$

Where y(k) is the output, and x(k) contains the nonlinear terms and w contains all the kernel coefficients:

$$w = [w_{o0,} w_{o1}(0), \ldots, w_{o1}(L-1) | w_{o2}(0,0), w_{o2}(1,0) \ldots w_{o2}(L-1, L-1)]^T \tag{2}$$

2.1 Volterra Series Algorithm

The Volterra series model is the most widely used model for nonlinear systems for several reasons. In particular, this model is useful for nonlinear adaptive filtering because the classical formulation of linear adaptive filters can be easily extended to fit this model. The Volterra series expansion of a nonlinear system consists of a nonrecursive series in which the output signal is related to the input signal as follows

$$\begin{aligned} d'(k) &= \sum_{l_1=0}^{\infty} w_{o1}(l_1)x(k-l_1) \\ &+ \sum_{l_1=0}^{\infty}\sum_{l_2=0}^{\infty} w_{o2}(l_1,l_2)x(k-l_1)x(k-l_2) \\ &+ \sum_{l_1=0}^{\infty}\sum_{l_2=0}^{\infty}\sum_{l_3=0}^{\infty} \ldots \\ &\sum_{l_i=0}^{\infty} w_{oi}(l_1,l_2,\ldots,l_i)x(k-l_1)x(k-l_2)\ldots x(k-l_i) \\ &+ \ldots \end{aligned} \tag{3}$$

Where $w_{oi}(l_1, l_2 \ldots, l_i)$ for i = 0, 1, . . . ,∞, are the coefficients of the nonlinear filter model based on the Volterra series, and d(k) represents, in the context of system identification application, the unknown system output when no measurement noise exists. The term $w_{oi}(l_1, l_2 \ldots, l_i)$ is also known as the Volterra kernel of the system. Note that the input signals in this case are assumed to consist of a tapped-delay line. For the general case, where the signals of the input signal vector come from different origins, such as in an antenna array, the Volterra series representation is given by

$$\begin{aligned} d'(k) &= \sum_{l_1=0}^{\infty} w_{o1}(l_1)x_{l_1}(k) \\ &+ \sum_{l_1=0}^{\infty}\sum_{l_2=0}^{\infty} w_{o2}(l_1,l_2)x_{l_1}(k)x_{l_2}(k) \\ &+ \sum_{l_1=0}^{\infty}\sum_{l_2=0}^{\infty}\sum_{l_3=0}^{\infty} \ldots \\ &\sum_{l_i=0}^{\infty} w_{oi}(l_1,l_2,\ldots,l_i)x_{l_1}(k)x_{l_2}(k)\ldots x_{l_i}(k) \\ &+ \ldots \end{aligned} \tag{4}$$

where $w_{oi}(l_1, l_2 \ldots, l_i)$, for i = 0, 1, . . . ,∞, are the coefficients of the nonlinear combiner model based on the Volterra series. As discussed by Mathews [1], the Volterra series expansion can be interpreted as a Taylor series expansion with memory. As such, the Volterra series representation is not suitable to model systems containing discontinuities on their models, as occurs with the Taylor series representation of functions with discontinuities. Another clear drawback of the Volterra series representation is the computational complexity, if the complete series is employed. By truncating the series one can reduce the computational complexity by sacrificing the accuracy of the series expansion. With reduced order, the Volterra series representation is quite complex even when the orders of the series and the filter are moderate.

2.1.1. Volterra Series Expansion of a Discrete Time Nonlinear System

The Volterra series model is the most widely used model in nonlinear adaptive filtering. The Volterra series expansion can be seen as a Taylor series expansion with memory. It consists of a non-recursive series in which the output signal is related to the input signal as follows:

$$y(k) = \sum_{l_1=0}^{N} w_{l_1}(k)x(k-l_1) + \sum_{l_1=0}^{N}\sum_{l_1=0}^{N} w_{l_1,l_2}(k)x(k-l_1)x(k-l_2) \tag{5}$$

The model is attractive in because the expansion is a linear combination of the nonlinear function of the input signal. The coefficients $w_{l_1}, w_{l_1,l_2} \ldots$ are the coefficients of a nonlinear combiner based on Volterra series, and called the Volterra series kernels (symmetric).

2.2. LMS Volterra Filter

The Volterra LMS algorithm is presented for a second-order series and Nth-order filter. This choice reduces the computational complexity to an acceptable level for some applications and also simplifies the derivations. The extension for higher-order cases is straightforward. The adaptive filter that estimates the signal $d'(k)$ using a truncated Volterra series expansion of second order, can be described by y(k),where w_{l_1} (k) and w_{l_1,l_2} (k), for l_1, l_2 = 0, 1, . . . , N, are the coefficients of the nonlinear filter model based on the second-order Volterra series expansion, and y(k) represents the adaptive-filter output signal.
The standard approach to derive the LMS algorithm is to use as estimate of the mean-square error (MSE) defined as

$$F[e(k)] = \xi(k) = E[e^2(k)] = E[d^2(k) - 2d(k)y(k) + y^2(k)] \tag{6}$$

the instantaneous square error given by

$$e^2(k) = d^2(k) - 2d(k)y(k) + y^2(k) \qquad (7)$$

Most of the analyses and algorithms presented for the linear LMS apply equally to the nonlinear but in LMS filter case, if we interpret the information and coefficient vectors and the adaptive-filter output is given by

$$y(k) = w^T(k)x(k) \qquad (8)$$

The estimate of the MSE objective function can now be rewritten as

$$e^2(k) = d^2(k) - 2d(k)w^T(k)x(k) + w^T(k)x(k)x^T(k)w(k) \qquad (9)$$

An LMS-based algorithm can be used to minimize the objective function as follows:

$$w(k+1) = w(k) - \mu\hat{g}_w(k)$$

$$= w(k) - 2\mu e(k)\frac{\partial e(k)}{\partial w(k)} \qquad (10)$$

for k = 0, 1, 2, . . ., where $\hat{g}_w(k)$ represents an estimate of the gradient vector of the objective function with respect to the filter coefficients. However, it is wise to have different convergence factors for the first- and second-order terms of the LMS Volterra filter. In this case, the updating equations are given by LMS Algorithm.

$$w_{l_1}(k+1) = w_{l_1}(k) + 2\mu e(k)x(k-l_1)$$

$$w_{l_1,l_2}(k+1) = w_{l_2}(k) + 2\mu e(k)\mu e(k)x(k-l_1)x(k-l_2) \qquad (11)$$

where l_1 = 0, 1, . . . , N and l_2 = 0, 1, . . . , N. As can be observed in Algorithm , the Volterra LMS algorithm has the same form as the conventional LMS algorithm except for the form of the input vector x(k). In order to guarantee convergence of the coefficients in the mean, the convergence factor of the Volterra LMS algorithm must be chosen in the range.

$$0 < \mu_1 < \frac{1}{t_r(R)} < \frac{1}{\lambda_{\max}}$$

$$0 < \mu_2 < \frac{1}{t_r(R)} < \frac{1}{\lambda_{\max}}$$

Where λ max is the largest eigen value of the input signal vector autocorrelation matrix.

$$R = E[x(k)x^T(k)] \qquad (12)$$

It should be noted that this matrix involves high-order statistics of the input signal, leading to high eigen value spread of the matrix R even if the input signal is a white noise. As a consequence, the Volterra LMS algorithm has in general slow convergence. As an alternative, we can consider implementing a Volterra adaptive filter using an RLS algorithm.

2.3. RLS Volterra Filter

The RLS algorithms are known to achieve fast convergence even when the eigen-value spread of the input vector correlation matrix is large. The objective of the RLS algorithm is to choose the coefficients of the adaptive filter such that the output signal y(k), during the period of observation, will match the desired signal as closely as possible in the least-squares sense. This minimization process can be easily adapted to the nonlinear adaptive filtering case by reinterpreting the entries of the input signal vector and the coefficient vector, as done in the LMS case.

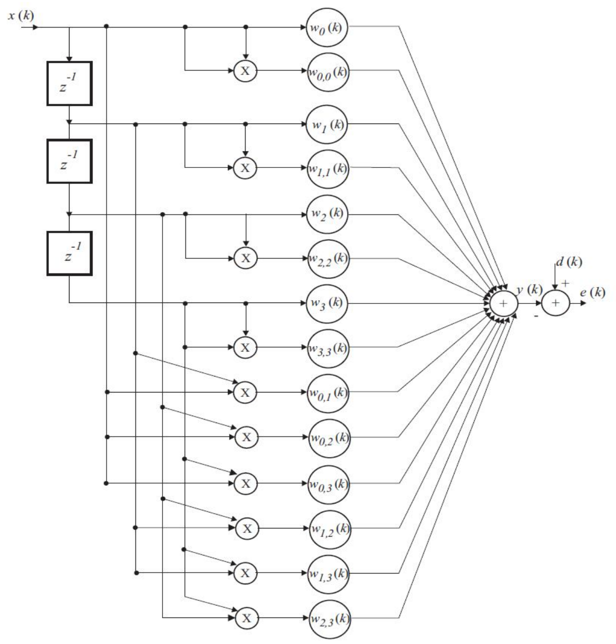


Fig.2 Adaptive Volterra Filter[3].

In the case of the RLS algorithm, the deterministic objective function is given by

$$\xi^d(k) = \sum_{i=0}^{k}\lambda^{k-1}\varepsilon^2(i)$$

$$= \sum_{i=0}^{k}\lambda^{k-1}[d(i) - x^T(i)w(k)]^2 \qquad (13)$$

where $\varepsilon^2(i)$ is the output error at instant i and are the input x(i) and the adaptive-filter coefficient vectors w(k). The parameter λ is an exponential weighting factor that should be chosen in the range 0 _ λ ≤ 1. By differentiating $\xi^d(k)$ with respect to w(k) and equating the result to zero, the optimal vector w(k) that minimizes the least-squares error can be shown to be given by

$$w(k) = \left[\sum_{i=0}^{k}\lambda^{k-i}x(i)x^T(i)\right]^{-1}\sum_{i=0}^{k}\lambda^{k-i}x(i)d(i)$$

$$= R_D^{-1}(k)p_D(k) \qquad (14)$$

where $R_D(k)$ and $P_D(k)$ are called the deterministic correlation matrix of the input vector and the deterministic cross-correlation vector between the input vector and the desired signal, respectively. The Volterra RLS algorithm has the same form as the conventional RLS algorithm as shown in RLS Algorithm, where the only difference is the form of the input vector x(k).

3. BROADBAND INTERFERENCE SUPPRESSION IN DSSS RECEIVER BY VOLTERRA FILTER

Direct sequence spread spectrum (DSSS) systems can operate in the presence of the strong co-channel interference if the processing gain is high enough. However, if this is not the case, or if the interference at the DSSS receiver is very strong, some additional means of the interference suppression has to be implemented. This paper contains block diagram of the proposed receiver is given and input signals are defined, results regarding the bit error rate are given. Proposed receiver is compared in performance to the receiver containing the ATF. Finally, the last section contains some concluding remarks.

3.1. RECEIVER MODEL

Block diagram of the proposed DSSS receiver containing the Volterra filter is presented at Fig. 1 Discretized total received signal x(n) is fed to the Volterra filter of the third order that contains the delay line with three taps. Signal y(n) at the filter output is given by,

$$y(n)=\sum_{i=1}^{1} a_i x(n-i)+\sum_{i=1}^{1}\sum_{j=1}^{1} b_{ij} x(n-i)x(n-j)+\sum_{i=1}^{1}\sum_{j=i}^{1}\sum_{k=j}^{1} c_{ijk} x(n-i)x(n-j)x(n-k) \quad (15)$$

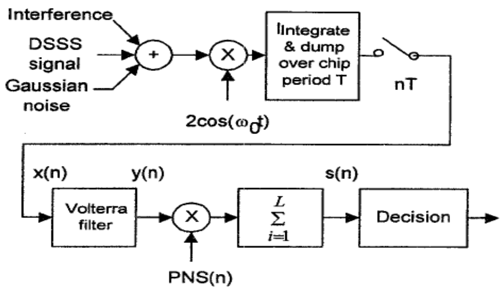


Fig.3- Block diagram of the proposed receiver; T-chip duration, L-processing gain[9].

where ai, bij, and cijk are the Volterra filter coefficients adapted by RLS algorithm. This algorithm is chosen for its robustness and very fast convergence in ATF applications. RLS adaptive algorithm has shown these same positive features in application on Volterra filter which is analyzed in this paper. Signal at the receiver input consists of three components.
First one is the desired DSSS signal, defined by,

$$u(t) = U.PNS(t)d(t)\cos(\omega_0 t) \quad (16)$$

where U and ω_0 mark the DSSS carrier and angular frequency, respectively, and PNS(t) is the pseudo noise sequence of chip duration T. Desired signal input power is Pu and its effective bandwidth is Bu. Message signal d(t)ϵ {+l,-1} with equal probabilily. Second input signal component is the interference i(n), modelled as the broadband BPSK signal,

$$i(t) = U_s d_s(t+\tau)\cos[(\omega_0 + 2\pi f_\Omega)t + \theta] \quad (17)$$

where U_s and f_Ω stand for the interference amplitude and carrier frequency offset to the BPSK carrier. Random data bit delay τ and initial carrier phase θ are uniformly distributed over the [(0, T)and(0,2π)] interval, respectively. Interference data bit ds(t)E [+1,-1} with equal probability. Its power at the receiver input is Ps and its effective bandwidth is Bs. As the measure of the Volterra filter performance in the broadband interference suppression, bit error rate (BER) is chosen. Based on the assumption that the de spreaded signal samples s(n) (Fig.3) are Gaussian distributed, BER is given by

$$BER = \tfrac{1}{2}\, erfc\left(\frac{E\{s(n)\}}{\sqrt{2\,\mathrm{var}\{s(n)\}}}\right) \quad (18)$$

Where mean, E{s(n)}, and variance, var{s(n)}, are obtained by the Monte-Carlo computer simulation. Fig.3. Presents BER as a function of the interference carrier offset fn normalized to the chip duration T. Relative interference bandwidth is Bu/Bs=0.37.

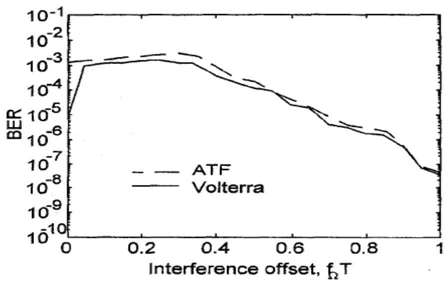


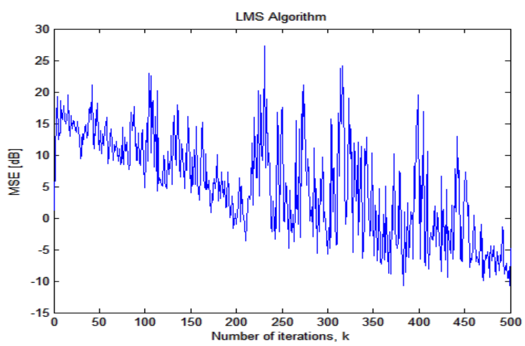
Fig.4- BER as a function of the normalized interference offset for Volterra and ATF receivers[9] .Input SIR=15dB, SNR=l2dB, Bu/Bs=0.37.

3.1.1. FIGURES AND TABLES

TABLE 1

LMS	Sx = 1	Sn = 0.1	Nw = 9
RLS	Sx = 1	Sn = 0.1	λ = 0.98

Where Sx is standard deviation of input, Sn is standard deviation of measurement noise, length of the adaptive filter, and lambda is exponential weighting factor.



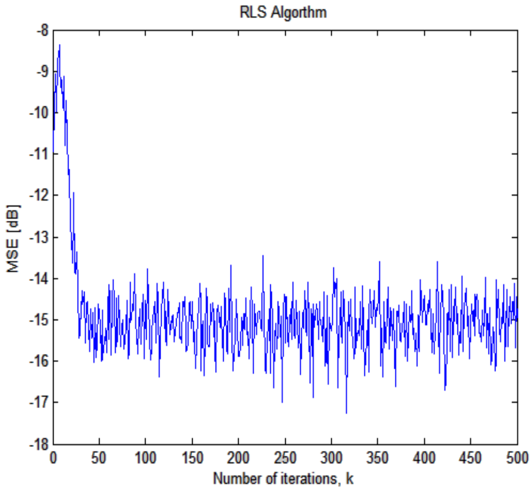


Fig. 5 Volterra filter LMS and RLS Algorithm.

4. CONCLUSION

In this paper the DSSS receiver performance with the Volterra filter and their algorithms used for the interference suppression is presented. Results, expressed by BER, show that the Volterra filter clearly outperforms the transversal filter in the broadband interference suppression process, thus enabling the DSSS signal reception even in the presence of the strong co-channel interference. This gives the opportunity of coexistence of classical broadband communication systems and DSSS systems in the same frequency band. In this case RLS algorithm is better than LMS algorithm cause of the tracking factor and convergence factor.

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