Narrowband Interference Rejection in GPS receiver using Adaptive Lattice Predictor

WEI-LUNG MAO
Department of Electronic Engineering
National Formosa University
Yunlin County,
Taiwan R.O.C.
wlmao@nfu.edu.tw

Abstract: - The global positioning system (GPS) provides accurate positioning and timing information useful in many applications. An adaptive lattice predictor for the anti-jamming purpose will be proposed. The adaptive filter is applied here to accurately predict the narrowband waveform based on an effective and computationally efficient stochastic-gradient algorithm. Simulation results show that our proposed fixed-point adaptive canceller achieves a better performance on narrowband interference rejection in GPS receiver.

Key-Words: - Adaptive Lattice Predictor, Stochastic-gradient Algorithm, Narrowband Interference Rejection, Global Positioning System(GPS)

1 Introduction

The GPS satellites broadcast ranging codes and navigation data with the technique of direct sequence spread spectrum (DS-SS). Although DS-SS inherently can cope with low power narrowband and wideband obstacles by its near 43-dB processing gain, it cannot cope with high power obstacles. The approaches of system performances that can be further enhanced by preprocessing to reject the intentional or unintentional jamming will be investigated in this paper.

The study of narrowband interference rejection has attracted considerable attention in recent years. Vijayan and Poor [3] proposed nonlinear methods of suppressing narrowband signals with a significant improvement in the signal-to-noise ratio (SNR). The approximate conditional mean (ACM) filter is applied to the narrowband interference, the statistics of which are known to the receivers. This approach produces better results than the linear Kalman filter. However, in practice, it is difficult to establish the autoregressive (AR) model. Therefore, they also proposed a new enhanced nonlinear adaptive (ENA) algorithm [4] that does not need the AR parameters and can outperform the existing linear and nonlinear adaptive filters. It is shown that ENA filter outperforms the linear/nonlinear adaptive filters. The artificial neural network (ANN) is one of the alternative methods used to achieve narrowband interference suppression in DS-SS [9]. The pipelined recurrent neural network, proposed by

Haykin and Li [11], provides a better SNR improvement than the nonlinear ACM filter when the statistics and number of code division multiple access (CDMA) users are unknown to those receivers. Several algorithms have been proposed for training of the recurrent neural network (RNN). The most widely known is the real time recurrent learning (RTRL) algorithm, proposed by Williams and Zipser [10], which can be used to update the weights of the RNN in real time.

In this paper, a fixed-point adaptive lattice predictor for the anti-jamming applications will be proposed. The received sample is given by r(k)=s(k)+n(k)+i(k), where the s(k) is the transmitted signal, the ambient white noise n(k) is modeled as white Gaussian noise, and the interference i(k) is modeled as having a bandwidth much less than the spread spectrum bandwidth. These three signal components are assumed to be mutually independent. The s(k) and n(k) sequences are wideband signals with nearly flat spectra. Thus, these two sequences cannot be estimated from their past values. Only the interfering signal i(k) can be predicted from its correlated property. The adaptive lattice filter is applied here to accurately predict the narrowband waveform based on a stochastic-gradient algorithm. The interference is then suppressed by subtracting the estimate from the actual received input. The interference-free signal will then be fed into the PN correlator.
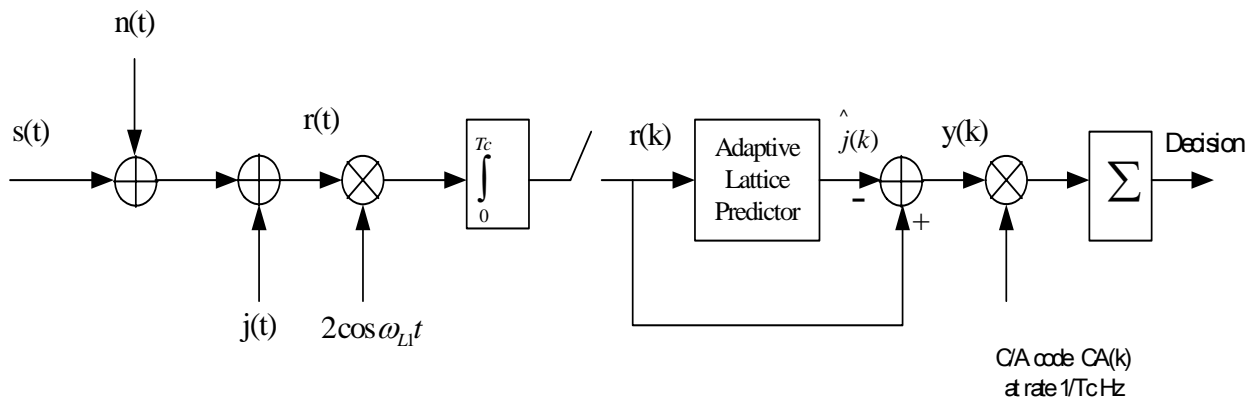
Fig 1. GPS anti-jamming system

The remainder of this paper is organized as follows. Section 2 describes the GPS received signal model. In Section 3, the detailed structure and learning algorithm of adaptive lattice filter are introduced. The simulation results are demonstrated in Section 4. Some conclusions are stated in the last section.

2 Jamming Signal Models

The GPS satellites broadcast ranging codes and navigation data at two frequencies: primary L1 (1575.42 MHz) and secondary L2 (1227.42 MHz), and only L1 signal, free for civilian use, is considered. A simplified block diagram of anti-jamming GPS receiver model is shown in Figure 1. The transmitted spread spectrum signal is given by

$$S(t) = [D(t) \oplus CA(t)]\cos(2\pi f_{L1}t + \theta) \qquad (1)$$

where $D(t)$ is binary data(± 1) from the satellite with duration T (T= 20ms). CA(t) represents the binary Gold Cold (± 1) with chip duration T_c ($R_C = 1/T_C = 1.023$MHz). f_{L1} and θ are L1 carrier frequency (1575.42MHz) and phase delay. The integer $PG = T/T_c = 20460 = 43$**dB** is the processing gain of GPS system.

The jamming signals may be friendly or intentional. Unintentional sources are originated from the RF transmitters, which are either on board the aircraft or nearby ground RF transmission stations. Intentional signals are always hostile. Four kinds of jamming signals are investigated:

(1) Single tone continuous wave interference (CWI):

$$j_1(k) = J \cos(\omega_\Delta kT_c + \theta) \qquad (2.1)$$

where J is amplitude and ω_Δ is its frequency offset from the center frequency of the spread spectrum signal. T_c is the chip duration, which is equal to the sampling interval. θ is a random phase uniformly distributed over the interval $[0,2\pi)$.

(2) Multi-tone CWI:

$$j_2(t) = \sum_{i=1}^{I} J_i \cos[\omega_{\Delta i}kT_c + \theta_i] \qquad (2.2)$$

where J_i, θ_i, and $\omega_{\Delta i}$ represent amplitude, random phase, and frequency offset, respectively, of the i-th interferer, and I is the number of narrowband interferers.

(3) swept (linear FM) CWI:

$$j_3(k) = J \cos[-(l-1)\omega_\Delta kT_c + 0.5 * \xi * (kT_c)^2 + \theta]$$

$$(l-1)K \le k < lK, l = 1,2,3,.... \qquad (2.3)$$

where J and θ are the amplitude and random phase of the swept CWI. ω_Δ represents the offset from the GPS carrier frequency, Ω is the sweep bandwidth, $\xi = \Omega/K$ is the sweep rate, and K is the sweep period.

(4) Pulsed CWI

$$j_4(k) = \begin{cases} J \cos(\omega_\Delta kT_c + \theta) & (l-1)N_T \le k < (l-1)N_T + N_1 \\ 0 & (l-1)N_T + N_1 \le k < lN_T \end{cases}$$

$$(2.4)$$

where the on-interval is $N_1 T_c$ seconds long and off-interval is $(N_T - N_1)T_c$ seconds long. We consider the case in which N_T and N_1 are much greater than unity.

The received signal is bandpass filtered, amplified and down converted. Due to the downconversion, the spectrum of signal is shifted to the baseband frequency. To further simplify the analysis, the received signal is sampled at the chip rate. The observation at sample k is

$$r(k) = S(k) + j(k) + n(k) \qquad (3.1)$$

where $n(k)$ is additive white Gaussian noise (AWGN) with variance σ^2. There are assumed to be mutually independent. The $n(k)$ can be modeled as band-limited and white, and the jamming source being considered has a bandwidth much narrower than $1/T_C$. The $S(k)$ sequence is $D(k) \oplus CA(k)$ taking values of ± 1. The S(k) and n(k), which are wideband signals, have nearly flat spectra. Thus, these two sequences cannot be estimated from their past values. The interference j(k), which is a narrowband signal, can be predicted because of its correlated property. The error signal $z(k)$ is obtained as:

$$z(k) = S(k) + n(k) + j(k) - \hat{j}(k) \cong S(k) + n(k) \quad (3.2)$$

$z(k)$ can be viewed as an almost interference-free signal and is fed into the correlator.

3 Proposed Adaptive Lattice Predictor

Fig. 2 shows the block diagram of the adaptive lattice predictor. The lattice filter have several advantages over direct form structure, which include low sensitivity to round off error, decoupling of filter type and so on. The input to the filer consists of the received sample waveform r(k).

$$\begin{cases} e_{f,i}(n) = e_{f,i-1}(n) - k_i(n)e_{b,i-1}(n-1) \\ e_{b,i}(n) = e_{b,i-1}(n-1) - k_i(n)e_{f,i-1}(n) \end{cases} ; \quad i = 1, 2, \cdots N \ (4)$$

with $e_{fi}(n)$ forward prediction error;

   $e_{bi}(n)$ backward prediction error;

   $k_i(n)$ reflection coefficient;

   i 0, 1, …N-1 for a filter of order N.

Since $r(n)$ may be considered as the zero-order forward and backward prediction errors, the initialization of above recursion is given by

$$r(n) = e_{f0}(n) = e_{b0}(n) \qquad (5)$$

For estimation of $k_i(n)$, we start with the cost function

$$J_i = E[e_{f,i}^2(n)] + E[e_{b,i}^2(n)] \qquad (6)$$

Substituting Eq. (4) into Eq. (6), we get :

$$\begin{aligned} Ji &= (1 + k_i^2(n))E\left[e_{f,i-1}^2(n) + e_{b,i-1}^2(n)\right] \\ &+ 4k_i(n)E\left[e_{f,i-1}(n)e_{b,i-1}(n)\right] \end{aligned} \qquad (7)$$

Differentiating the cost function Ji with respect to the complex-valued reflection coefficients $k_i(n)$, we get:

$$\begin{aligned} \frac{\partial J_i}{\partial k_i} &= 2k_i(n))E\left[e_{f,i-1}^2(n) + e_{b,i-1}^2(n)\right] \\ &+ 4E\left[e_{f,i-1}(n)e_{b,i-1}(n)\right] \end{aligned} \qquad (8)$$

Putting this gradient equal to zero, we find the optimum value of the reflection coefficient for which the cost function J_i is minimum equals

$$k_i^* = -\frac{2E[e_{f,i-1}(n)e_{b,i-1}(n-1)]}{E[e_{f,i-1}^2(n)] + E[e_{b,i-1}^2(n-1)]} \qquad (9)$$

The stochastic-gradient adaptive algorithm adapts $k_i(n)$ to minimize

$$J_i(n) = e_{f,i}^2(n) + e_{b,i}^2(n) \qquad (10)$$

Expressing $J_i(n)$ in terms of $e_{f,i-1}(n)$ and $e_{b,i-1}(n)$, and $k_i(n)$, and taking the derivative of $J_i(n)$ with respect to $k_i(n)$, we have :

$$\begin{aligned} \frac{\partial J(n)}{\partial k_i(n)} &= \frac{\partial e_{f,i}^2(n)}{\partial k_i(n)} + \frac{\partial e_{b,i}^2(n)}{\partial k_i(n)} \\ &= -2[e_{f,i-1}(n) - k_i(n)e_{b,i-1}(n-1)]e_{b,i-1}(n-1) \quad (11) \\ &- 2[e_{b,i-1}(n-1) - k_i(n)e_{f,i-1}(n)]e_{f,i-1}(n) \end{aligned}$$
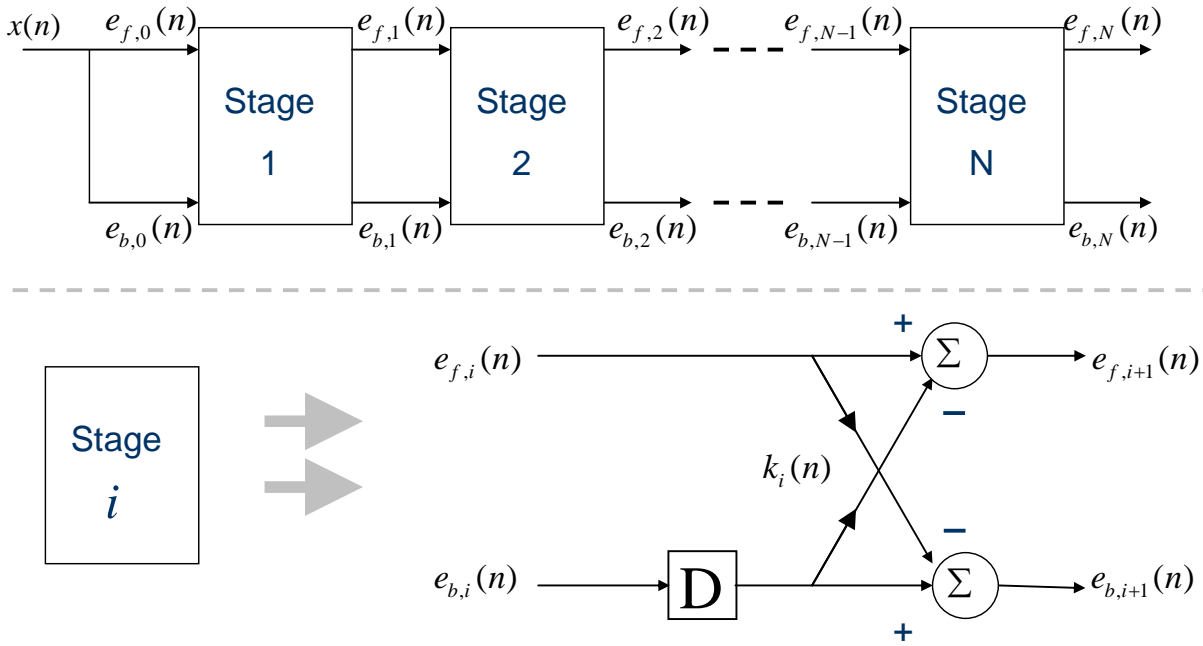
The update equation is written as :

Fig. 2 Block diagram of the stochastic-gradient adaptive lattice predictor

$$k_i(n+1) = k_i(n) - \frac{\beta_i(n)}{2} \frac{\partial J(n)}{\partial k_i}$$

$$= k_i(n)\{1 - \beta_i(n)[e_{f,i-1}^2(n) + e_{b,i-1}^2(n-1)]\} \quad (12)$$

$$+ 2\beta_i(n)e_{f,i-1}(n)e_{b,i-1}(n-1)$$

where $\beta_i(n)$ is the adaptation constant. For the speed of adaptation to be relatively independent of the input signal levels, the step size $\beta_i(n)$ needs to be normalized by an estimate of the sum of the $(i-1)$-th order prediction error variance. Hence, we can write :

$$\beta_i(n) = \frac{1}{S_{i-1}(n)} \quad (13)$$

where $S_{i-1}(n)$ is estimated recursively as

$$S_{i-1}(n+1) = (1-\alpha)S_{i-1}(n) + e_{f,i-1}^2(n) + e_{b,i-1}^2(n-1) \quad (14)$$

where α is a constant, which, in conjuction with the initial value of $S_{i-1}(n)$ controls the speed of adaptation. The stochastic-gradient adaptive algorithm is completely described by the following equations:

$$k_i(n+1) = \left\{1 - \beta_i(n)\left[e_{f,i-1}^2(n) + e_{b,i-1}^2(n-1)\right]\right\} \quad (15.1)$$

$$+ 2\beta_i(n)e_{f,i-1}(n)e_{b,i-1}(n-1)$$

$$S_{i-1}(n+1) = (1-\alpha)S_{i-1}(n) + e_{f,i-1}^2(n) + e_{b,i-1}^2(n-1) \quad (15.2)$$

$$\beta_i(n) = \frac{1}{S_{i-1}(n)} \quad (15.3)$$

$$e_{f,i}(n) = e_{f,i-1}(n) - k_i(n)e_{b,i-1}(n-1) \quad (15.4)$$

$$e_{b,i}(n) = e_{b,i-1}(n-1) - k_i(n)e_{f,i-1}(n) \quad (15.5)$$

4 SIMULATION RESULTS

The simulation results of the stochastic-gradient adaptive canceller are obtained by using Matlab tool to verify the performances. The received signal is bandpass filtered, amplified and down converted to IF and then digitized. The IF is fixed at 1.25 MHz, and a sampling frequency of 5 MHz is selected. A 10th order adaptive lattice filter is developed and the bit number of each tap is 29. The metric used to verify the steady state performance of adaptive filters is the "SNR improvement", which was defined in [3] and given by:

$$\mathbf{SNR}_{improvemnt} = 10\log[E|r(k) - S(k)|^2 / E|y(k) - S(k)|^2](\mathbf{dB}) \quad (16.1)$$

where $y(k)$ is the prediction error of the adaptive filter. The SNR improvement represents the ratio of

SNR at the output of the filter to the SNR at input. The SNR at input of the filter is defined as follows:

$$\mathbf{SNR}_{input} = 10\log[E|S(k)|^2 / E|r(k) - S(k)|^2](\mathbf{dB}) \ (16.2)$$

The SNR at output of the filter is given by

$$\mathbf{SNR}_{output} = 10\log[E|S(k)|^2 / E|y(k) - S(k)|^2](\mathbf{dB}) \ (16.3)$$

where $S(k)$ is baseband GPS spreading signal, i.e. $D(k) \oplus CA(k)$. In our simulation, $D(k)$ was binomially distributed with value of ± 1, and $CA(k)$ was randomly chosen with equal probability from 24 PRN codes of GPS system. The variance of background thermal noise $n(k)$ was held constant at $\sigma^2 = 0.01$ relative to the signal $S(k)$, the power of which is 1.0. The simulation results were obtained based on 30 trials, and in each trial 2000 data points were computed. The single tone CWI offset frequency is set to $\omega_{off} = 1.2 * 2\pi$ MHz. The multi-tone CWI offset frequencies are set to 0.8 MHz and 1.2MHz. The relative sweep rate is set to 10 MHz/sec in swept CWI test. The starting frequency is 0.25MHz and the ending frequency is 1.25 MHz. In pulsed CWI condition, the on-interval $N_1 T_c$ is chosen as 0.005 sec and off-interval is 0.005 sec.

Table I: SNR improvement (d**B**) for various types of interference signals

Interference Types	Interference Noise Ratio (INR) (d**B**)			
	50	40	30	20
	SNR improvement ratio (dB)			
Single tone CWI	49.16	40.79	31.33	21.53
Multi-tone CWI	48.25	39.12	30.16	21.29
Swept CWI	47.27	39.07	30.28	20.69
Pulsed CWI	33.42	32.03	26.86	21.11

The results on SNR improvements are summarized in Table I. To illustrate the ability of adaptive filter in the diverse CWI environments, the input INR is varied from 20**dB** to 5**dB**. It can be seen that our scheme offers considerable advantage. On average, the proposed adaptive lattice filter achieves 35.74dB, 34.71dB, 34.32dB and 28.36dB of SNR improvements under the CWI, MCWI, SCWI, and PCWI conditions, respectively. Finally, a fixed-point

adaptive lattice canceller is successfully simulated and evaluated for narrowband interference suppression in GPS receiver.

5 Conclusions

In this paper, an adaptive lattice predictor architecture is used to suppress the narrowband interference in GPS receivers. The adaptive canceller provides a powerful structure for adaptive filtering of stationary/nonstationary time series. For comparison of the interfering signals, four cases are considered, i.e., (1) single tone CWI signal, (2) multi-tone CWI signal, (3) swept CWI and (4) pulse CWI. The SNR improvement is chosen as a metric to demonstrate the steady state performance. Simulation results show that our method can achieve superior SNR improvement performances. On average, the proposed lattice filter achieves 35.74dB, 34.71dB, 34.32dB and 28.36dB of SNR improvements under the CWI, MCWI, SCWI, and PCWI conditions, respectively. The proposed anti-jamming architecture can be also used in spread spectrum system and navigation system.

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