非線可適性預估器在 GPS 接收機窄頻抗干擾信號處理之應用

Narrowband Interference Suppression in GPS Receivers Using Nonlinear Adaptive Predictors

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摘要

全球定位系統接收機已被廣泛使用在各種商用與軍用的系統中，而在通訊中干擾信號的發生是無法避免的。本研究針對兩種窄頻帶信號(即單頻干擾與掃頻干擾) 環境下，利用非線性可適預估器來達成抗干擾的成效。非線性可適濾波器包含管線式回授類神經網路與延遲濾波器兩個部分。我們利用梯度下降演算法與最小平方平均演算法來即時調整其權重參數。模擬結果可知我們提出的方法可比傳統的線性濾波器法得到較好的信號雜訊改善比。

關鍵詞：全球定位系統接收機，窄頻干擾，管線式回授類神經網路，延遲濾波器

ABSTRACT

Commercial global positioning system (GPS) receivers are susceptible to be jammed due to the presence of interference signals. In this paper, two kinds of jamming signals are investigated: (a) continuous wave interference (CWI) and (2) swept CWI. A nonlinear adaptive predictor (NAP), which consists of two subsections: a pipelined recurrent neural network (PRNN) and a conventional tapped delay line filter, is used to suppress the narrowband interference signal. The gradient descent (GD) and least mean square (LMS) algorithms are adopted to update the synaptic weights. Simulation results show that our method can indeed achieve a superior signal-to-noise ratio (SNR) performance relative to the conventional linear adaptive filter.

Keywords： global positioning system (GPS) receiver, narrowband interference, pipelined recurrent neural network, and tapped delay line (TDL) filter.

1. Introduction

The GPS system supply service to an unlimited number of consumers in the world by using direct sequence spread spectrum (DS-SS) techniques. It spreads the bandwidth of transmitting signals with C/A code that results in a 43dB processing gain. Thus, DS-SS technique inherently exhibits anti-jamming property that can cope with narrowband interference. However, when the jamming power is high level, it is necessary to supplement the innate processing gain by using additional signal processing techniques such as adaptive filters. A number of useful adaptive filter algorithms have been published over the last decade. It has been demonstrated that the performance of DS-SS system can be enhanced through the use of adaptive filters prior to despreading [1-2]. Linear adaptive architectures are not powerful enough to predict these stationary/ nonstationary signals.

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Vijayan and Poor proposed nonlinear methods of suppressing narrowband signal with significant increase in the SNR improvement. The approximate conditional mean (ACM) filter and enhanced nonlinear adaptive (ENA) filter are proposed to estimate the jamming signals. It is shown that ENA filter outperforms the linear/nonlinear adaptive filters.

An artificial neural network is one of the alterative methods to achieve narrowband interference suppression in DS-SS [6]. The pipelined recurrent neural network, which is proposed by Haykin and Li [9], provides a better SNR improvement than ENA filters do when the statistics and number of CDMA users are unknown to those receivers.

In this paper, a computationally efficient nonlinear adaptive predictor (NAP) based on a PRNN and a linear TDL filter [3-4] has been investigated. Simulation results show that our method can offer superior SNR performance relative to the TDL filters.

The remainder of this paper is organized as follows. Section II describes the GPS received signal model. In Section III, the detailed structure and learning algorithm of NAP are introduced. The simulation results are demonstrated in Section IV to compare NAP and TDL filter. Some conclusions are stated in the last section.

2. Received Signal Models

The 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 civil purpose is considered. A simplified block diagram of anti-jamming GPS model is shown in Figure 1. The GPS transmitted signal is given by:

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

where $D(t)$ is binary data of the satellite containing navigation message with a duration of T (T= 20ms). $CA(t)$ is binary Gold Code with chip duration T_c

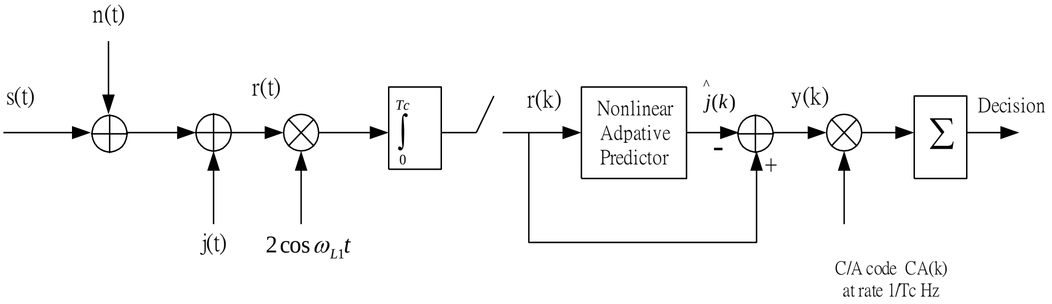

Fig 1. GPS anti-jamming system

($R_C = 1/T_C = 1.023MHz$). f_{L1} and θ are L1 carrier frequency (1575.42 MHz) and phase delay.

The jamming signals may be friendly or intentional. Unintentional source is originated form the RF transmitter, either on board the aircraft or nearby ground RF transmission stations. Intentional obstacle is always hostile. Two kinds of jamming signals are investigated: a single tone CWI and a periodically swept (linear FM) CWI, which can be expressed as

(a) CWI case:

$$j_1(t) = J\cos[(\omega_{L1} + \omega_{off})t + \varphi] \qquad (2)$$

where J is amplitude, ω_{off} is the offset frequency relative to the GPS carrier frequency, and φ is a random phase uniformly distributed over interval $[0,2\pi)$.

(b) Swept CWI case:

$$j_2(t) = J\cos[\omega_{L1} * t - (l-1)\Omega * t + 0.5 * \xi * t^2 + \varphi]$$
$$(l-1)T_j \le t \le lT_j \qquad (3)$$

where J and φ are the amplitude and random phase of the CWI. Ω is the sweep bandwidth, $\xi = \Omega / T_j$ is the sweep rate, T_j is the sweep period.

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

$$r(k) = S(k) + j(k) + n(k) \qquad (4)$$

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 smaller compared with $1/T_C$. 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 spectrum. So these two sequence cannot be estimated from their past value. The interference j(k), which is a narrowband signal, can be predicted because of its correlated property.

3. Proposed Nonlinear Adaptive Predictor

The prediction of a time series is synonymous with modeling of physical systems responsible for its generation. However, the jamming signals always have statistically nonstationary properties, and one nonlinear structure suitable for estimation is the neural networks. In this paper, a NAP (in Fig 2) is employed to suppress the jamming signal. These two subsections offer distinct functions. The PRNN performs a nonlinear mapping from input space to an intermediate space with the aim of linearing the input signal. The TDL performs a linear mapping from a new intermediate space to the output space. Both of these operations are performed adaptively on a continuous basis.

A. Nonlinear Subsection

The PRNN is composed of M identical modules. Each module consists of a fully connected RNN with N neurons. Fig 3 shows the detailed structure of module i with P external inputs, N neurons, and one bias input with a value of $+1$. Each module has (N-1) neuron outputs fed back to its input, and the remaining neuron output (the first neuron output) is applied directly to the next module. In the case of module M, the first neuron output is assumed to feed back to the input itself. For the i-th module, the input vector consisting of (P+N+1) input signals can be represented as

$$\mathbf{u}_i^T = [r(k-i),..,r(k-i-P+1),1,x_{i+1,1}(k),x_{i,2}(k-1),..,x_{i,N}(k-1)]^T$$
$$\text{for } 1 \le i \le M-1 \qquad (5)$$

$$\mathbf{u}_i^T = [r(k-i),.....,r(k-i-P+1),1,x_{i,1}(k),x_{i,2}(k-1),.....,x_{i,N}(k-1)]^T$$
$$\text{for } i = M \qquad (6)$$

where $x_{i,j}(k)$ is j-th internal feedback signal of module i at k-th time point.

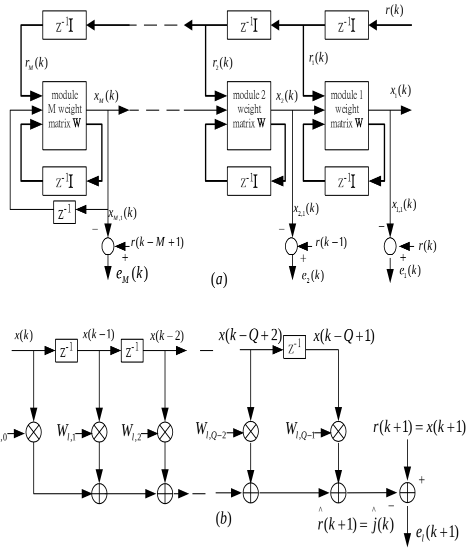

Fig 2. (a) Pipelined recurrent neural network,
(b) Tapped delay line filter

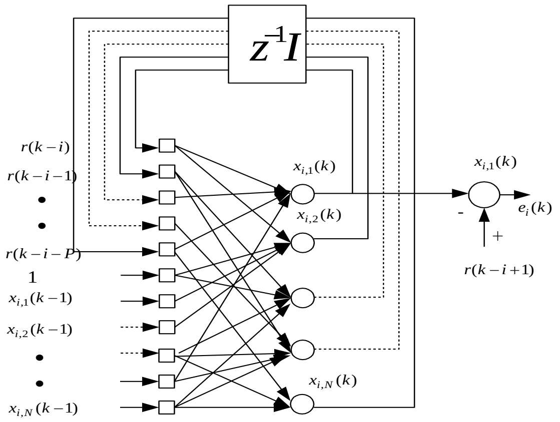

Fig. 3 Detailed construction of module i of PRNN

Let $\mathbf{W}$ denotes the (P+N+1)-by-N synaptic weight matrix for each module. An element $w_{i,j}$ of this matrix represents the weight of the connection to the i-th neuron form the j-th input node. The vector can be described as

$$\mathbf{W} = [\mathbf{w}_1,....\mathbf{w}_N] \tag{7}$$

$$\mathbf{w}_k^T = [w_{k,1},.....,w_{k,(P+N+1)}] \tag{8}$$

The nonlinear function $\psi(\bullet)$ represents the sigmoid activation function for all neurons in the network, and defined as

$$\psi(v) = \tanh(\frac{a*v}{2}) = \frac{1-e^{-av}}{1+e^{-av}} \tag{9}$$

where a is the gain of the neuron. The complete description of PRNN is given by

$$x_{i,m}(k) = \Psi(v_{i,m}) \tag{10}$$

$$v_{i,m}(k) = \sum_{l=1}^{P+N+1} w_{m,l}(k) u_{i,l}(k) \tag{11}$$

where $v_{i,m}$ is the internal activation of m-th neuron within i-th module, and $x_{i,m}(k)$ is the output of the m-th neuron in module i. Given the input vector $\mathbf{u}_i$ for each module i (i=1,…M), the outputs of all neurons in the network at the time step k can be computed from Eq. (10) and (11). The output of module i is defined as the output of its first neuron $x_{i,1}$. Hence, the prediction error for module i is given by

$$e_i(k) = r(k-i+1) - x_{i,1}(k) \tag{12}$$

where $e_i(k)$ denotes the one-step prediction error of module i. The overall cost function E(k) of the PRNN is defined by

$$E(k) = \sum_{i=1}^{M} \lambda^{i-1} e_i^2(k) \tag{13}$$

where λ is the forgetting factor that lies in the range $0 < \lambda \le 1$.

Gradient descent learning algorithm

A gradient descent learning algorithm that updates the PRNN synaptic weights is following the approach of [9]. The change for the l-th weight of neuron m at time step k, can be expressed as

$$\begin{aligned} \Delta w_{m,l}(k) &= -\eta \frac{\partial E(k)}{\partial w_{m,l}} \\ &= -2\eta \sum_{i=1}^{M} \lambda^{i-1} e_i(k) \frac{\partial e_i(k)}{\partial w_{m,l}(k)} \end{aligned} \tag{14}$$

where η is a fixed learning rate parameter lying in the range $(0,1]$. The partial derivative of the instantaneous error $e_i(k)$ respects with the weight $w_{m,l}$ becomes

$$\frac{\partial e_i(k)}{\partial w_{m,l}(k)} = -\frac{\partial x_{i,1}(k)}{\partial w_{m,l}(k)} \tag{15}$$

Using the chain rule, the last equation becomes

$$\begin{aligned} \frac{\partial x_{i,1}(k)}{\partial w_{m,l}(k)} &= \frac{\partial x_{i,1}(k)}{\partial v_{i,1}(k)} \frac{\partial v_{i,1}(k)}{\partial w_{m,l}(k)} \\ &= \dot{\Psi}(v_{i,1}(k)) \frac{\partial v_{i,1}(k)}{\partial w_{m,l}(k)} \end{aligned} \tag{16}$$

where $\dot{\Psi}(\bullet)$ is the first derivative of the activation function $\Psi(\bullet)$ with respect to its argument, which is the internal activity of the first neuron in the i-th module $v_{i,1}$. The $\partial v_{i,1} / \partial w_{m,l}$ is substituted and yields

$$\frac{\partial x_{i,1}(k)}{\partial w_{m,l}(k)} = \dot{\Psi}(v_{i,1}(k))\left(\sum_{\alpha-1}^{N}\frac{\partial x_{i,\alpha}(k)}{\partial w_{m,l}(k)} + \delta_{m,l}u_{i,l}(k)\right) \tag{17}$$

where $\delta_{m,l}$ is equal to 1 when $m = l$, and zero otherwise. Form (12) and (13), the change applied to the (m,l)-th element of the synaptic weight matrix is according to

$$\Delta w_{m,l}(k) = 2\eta\sum_{i=1}^{M}\lambda^{i-1}e_i(k)\frac{\partial x_{i,1}(k)}{\partial w_{m,l}(k)} \tag{18}$$

Using the GD algorithm on the cost function, the correction matrix $\Delta\mathbf{W}(k)$ is computed. This term is added to the weight matrix $\mathbf{W}(k)$ to form the updated weight matrix $\mathbf{W}(k+1)$:

$$\mathbf{W}(k+1) = \mathbf{W}(k) + \Delta\mathbf{W}(k) \tag{19}$$

Using the updated weight matrix $\mathbf{W}(k+1)$ and the updated input vector $\mathbf{u}_i$, the output vector $x_i(k)$ of module i can be computed.

B. LINEAR SUBSECTION

The output variable of PRNN, $x_{1,1}(k)$, is then fed into the tapped delay line filter to accomplish the one step prediction. The linear subsection is a conventional linear predictor using normalized LMS algorithm to update the adjustable weights. The normalized LMS algorithm is expressed as

$$e(k) = r(k+1) - \mathbf{W}_1^T(k)\mathbf{X}_l(k) \tag{20}$$

$$\mathbf{W}_l(k+1) = \mathbf{W}_l(k) + \frac{\mu_0}{h_k}e(k)\mathbf{X}_l(k) \tag{21}$$

$$\mathbf{X}_l(k) = [x(k), x(k-1), \ldots., x(k-Q+1)]^t$$

where $e(k)$ denotes the one-step prediction error of NAP, and is then sent to the GPS SS detector. μ_0 is the step-size parameter of the normalized LMS algorithm, and it is chosen small enough to ensure the convergence. h_k is an estimate of the input power, that can be determined by

$$h_k = \alpha h_{k-1} + (1-\alpha)r_{k+1}^2 \tag{22}$$

where α is a forgetting factor that lies in the range $0 < \alpha \le 1$. It is chosen to yield a compromise between the prediction accuracy and the tracking capability.

4. Simulation Results

The metric used to verify the steady state performance of adaptive filters is the "SNR improvement ratio", which is defined in [3] and given by

$$\mathbf{SNR}_{improvemnt} = 10\log[E|r(k) - S(k)|^2 / E|y(k) - S(k)|^2](\mathbf{dB}) \tag{23}$$

where $y(k)$ is the prediction error of the NAP filter. It represents the ratio of SNR in suppressing the interference at the output of the filter to the SNR at input. The SNR ratio at input of the filter is defined as follows:

$$\mathbf{SNR}_{input} = 10\log[E|S(k)|^2 / E|r(k) - S(k)|^2](\mathbf{dB}) \tag{24}$$

The SNR ratio at output of the filter is given by

$$\mathbf{SNR}_{output} = 10\log[E|S(k)|^2 / E|y(k) - S(k)|^2](\mathbf{dB}) \tag{25}$$

where $S(k)$ is baseband GPS spreading signal combined with navigation message data $D(k)$ modulated by C/A code, i.e. $D(k) \oplus CA(k)$. In our experiments, $D(k)$ was binomially distributed with value of ± 1, and $CA(k)$ was randomly chosen with equal probability form 24 PRN code. The variance of background thermal noise $n(k)$ was kept constant at $\sigma^2 = 0.01$ relative to a unit power S(k) signal.

In our simulation, the results were obtained based on 30 trials, and for each trial 2000 data points were computed. The CWI offset frequency is set to $\omega_{off} T_c = 0.6$ and the power of the AWGN noise was 0.01 relative to a unit power S(k) signal. The relative sweep bandwidth (B_S / B_C) is set to 0.1 and the relative sweep rate (R_S / R_C) is set to 2000. The parameters of NAP are M=5, N=2 and Q=10, respectively.

Fig. 4 shows the SNR improvement ratio curve versus input SNR. To illustrate the ability of NAP in diverse CWI environment, the input SNR is varied from –20dB to –5dB. It can be seen that the NAP offers considerable advantage over conventional TDL filter. The performance of linear filter is always worse than that of NAP. In average, NAP provides 8.74dB in term of SNR improvement ration than TDL method does.

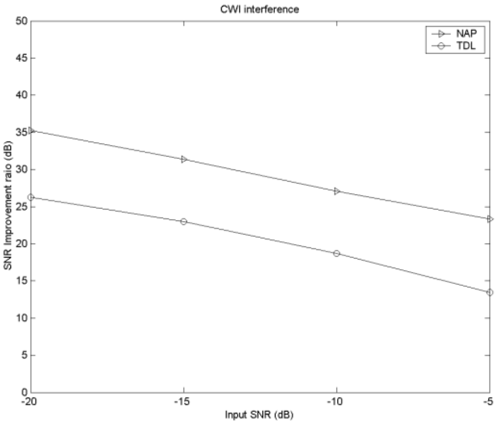

Fig 4: SNR improvement ratio (d**B**) for CWI interference

Another jamming signal considered is swept CWI with nonstationary property. The frequency of swept CWI increases linearly at the beginning of each interval, and reset at the end of interval. Fig. 5 plots the SNR improvement ratio versus input SNR. The NAP is suitable for predicting nonstationary signal and offers 8.3dB in terms of SNR improvement ratio than that achieved by TDL in average.

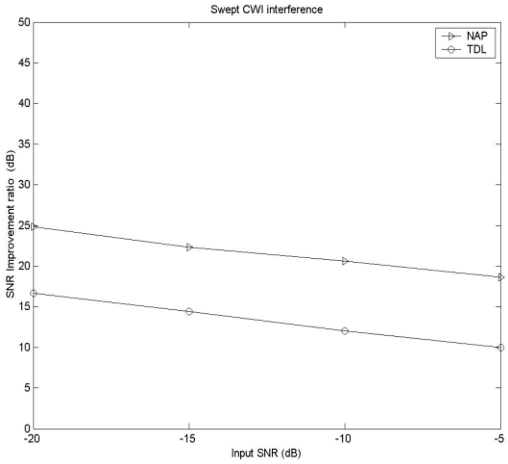

Fig 5: SNR improvement ratio (d**B**) for swept CWI interference

5. CONCLUSIONS

In this paper, the NAP based on PRNN and TDL architecture is used to suppress the narrowband interference in GPS receiver. The NAP provides a powerful structure for nonlinear adaptive filtering of stationary/nonstationary time series. For comparison of the interfering signals, two cases are considered, i.e., (1) CWI signal, and (2) swept CWI. The SNR improvement ratio is chosen as a metric to demonstrate the steady state performance. Simulation results show that the NAP can achieve a superior SNR improvement performance to that of TDL filter. Moreover, the additional gain provided by the NAP over the TDL is approximately 8.5 dB.

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