Narrowband Interference Cancellation using Set-membership Adaptive Predictor for GPS Receiver

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Abstract—**The global positioning system (GPS) provides accurate positioning and timing information that is useful in various civil and military applications. The adaptive filtering predictor for GPS jamming suppression applications is proposed. This research uses the gLab-G software to substitute for the hardware receiver to record the GPS signal waveform. The normalized least-mean-square (NLMS) and set-membership NLMS (SM-NLMS) filtering methods are employed for continuous wave interference suppression. Simulation results reveal that our proposed methods can provide the better performances when the interference-to-noise ratios (INR) are varied from 20 to 50 dB. The anti-jamming performances are evaluated via extensive simulation by computing mean squared prediction error (MSPE) and signal-to-noise ratio (SNR) improvements.**

Keywords—global positioning system (GPS); gLab-G; adaptive filtering algorithms; normalized least-mean-square (NLMS); set-membership NLMS (SM-NLMS).

I. Introduction

The global positioning system (GPS) [1, 2] can provide accurate positioning and timing information useful in many applications. The satellites in this system supply service to consumers by using direct sequence spread spectrum (DS-SS) techniques. GPS spreads the bandwidth of transmitting signals with coarse/acquisition (C/A) code, which results in a 43dB processing gain. Thus, DS-SS technique inherently exhibits a modest anti-jamming property that can cope with narrowband interference. However, when the jamming power is high, it is necessary to supplement the innate processing gain by using additional signal processing techniques such as adaptive filters. It has been demonstrated [3-7] that the capability of DS-SS to reject narrowband interference can be further improved by using adaptive filters prior to despreading. These jamming sources can be inherently stationary/nonstationary and associated high order statistics, so nonlinear adaptive filters may be more suitable to the prediction of these jamming signals.

The study of the adaptive filter used in the anti-jamming has attracted considerable attention in recent years. Although the set-membership normalized least-mean-square(SM-NLMS) algorithm may be seen as a generalization of thewell-known normalized least-mean-square (NLMS) algorithm, it inherits some desired features of the set-membership filtering (SMF) approach. The SMF algorithms are able to combat conflicting requirements such as fast convergence and low misadjustment by introducing a modification on the objective function. In addition, these algorithms exhibit reduced complexity due to data-selective updates, which involve two steps: a) information evaluation and b) update of parameter estimates [18]. Some of these features are: robustness against noise, reduced number of arithmetic operations (especially after convergence) and lower steady-state mean square error (MSE) if the parameters are properly chosen [8, 9]. Many papers have confirmed these good features of SM algorithms in a number of applications such as interference suppression for CDMA systems [10], the available literature on this topic has always shown that the SM algorithms outperform their non-SM counterparts [9]. In most articles solely explained the merit and adjustment of the coefficients for adaptive filter, compared with few makes the analysis and comparison in view of the merge of NLMS and SM-NLMS methods. More concrete explanation, since these algorithms have some same coefficient hypotheses, it would be useful to come up with some guidelines to set the parameters in order to achieve a good performance [9], afterward compares two kinds of filter SNR and MSPE.

II. Received Signal Models

GPS systems are continuously going through progressive evolution in the field of positioning and navigation. A receiver computes its position, velocity and time solution by processing received data from a constellation of satellites. Unfortunately, the low power GPS signal is susceptible to many types of interference, which can be either intentional or unintentional. This interference can degrade the quality of, or totally disable some of, the processes in the GPS receivers.

The satellites broadcast ranging codes and navigation data at two frequencies: primary L1 and secondary L2, and only the L1 signal, free for civilian use, will be considered. A simplified block diagram of an anti-jamming GPS model is shown in Fig. 1. The transmitted spread spectrum signal is

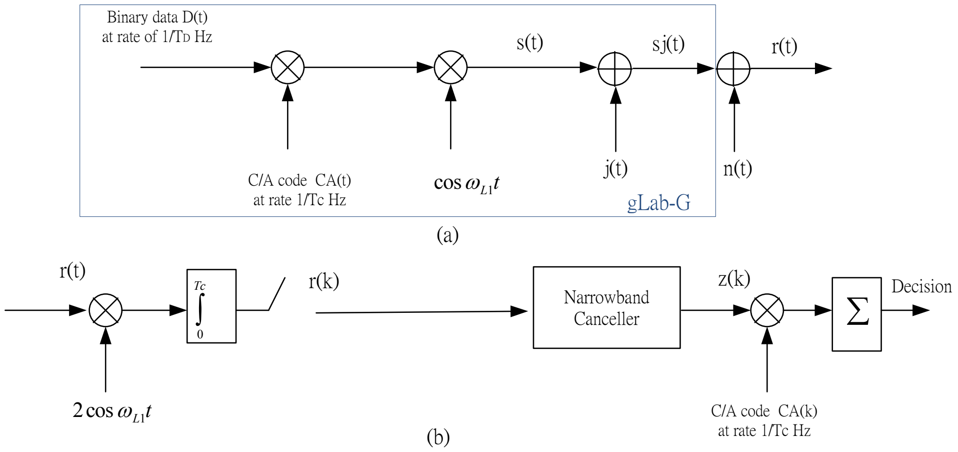


Fig. 1. GPS spread spectrum system (a) The transmitter is generate by gLab-G software, (b) Anti-jamming receiver.

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

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

The received signal $r(t)$ can be modeled as

$$r(t) = S(t) + n(t) + j(t) \qquad (2\text{–}1)$$

where $n(t)$ is additive white Gaussian noise (AWGN) with variance σ^2, and the jamming source $j(t)$ has a bandwidth much smaller than the GPS spreading bandwidth.

The received signal is bandpass filtered, amplified and down converted. Due to the downconversion, the spectrum of the signal is shifted to the baseband frequency. To further simplify the analysis, we assume that the received signal passes through a filter matched to the chip waveform and is sampled synchronously once during each chip interval. The observation

$$r(k) = S(k) + n(k) + j(k) \qquad (2\text{–}2)$$

where $\{S(k)\}$, $\{n(k)\}$ and $\{j(k)\}$ are discrete time sampled waveform of $\{S(t)\}$, $\{n(t)\}$, and $\{j(t)\}$, respectively. They 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 $\pm$ 1.

The low power jamming signal can be suppressed by GPS receivers with the 43dB processing gain (C/A code). However, if strong jamming signals are present, they can result in degradation of navigation accuracy or even complete loss of receiver tracking. In this project, the single tone continuous wave interference (CWI) is considered:

$$j(k) = J\cos(\omega_\Delta kT_c + \theta) \qquad (3)$$

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 $[0, 2\pi)$.

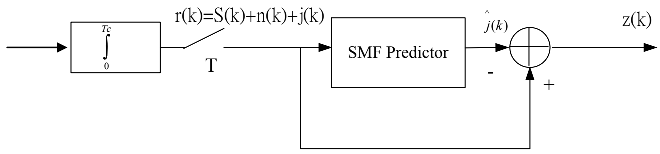


Fig. 2. Narrowband canceller block diagram

In Fig. 2, the narrowband canceller composed of an RNN predictor and an adder is employed to suppress the jamming signals. 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. The interfering signal $\{j(k)\}$ can be predicted because of its correlated property. The error signal $z(k)$ is obtained as

$$z(k) = S(k) + n(k) + j(k) - \hat{j}(k) \cong S(k) + n(k) \qquad (4)$$

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

III. Adaptive Filtering Algorithms

The basic assumption is that the additional noise is considered bounded, and the bound is either known or can be estimated [11]. The key strategy of the formulation is to find feasibility set such that the bounded error specification is met for any member of this set. As a result, the set-membership filtering (SMF) is aimed at estimating the feasibility set itself or a member of this set [12]. The SMF allows the reduction of computational complexity in adaptive filtering, since the filter coefficients are updated only when the output estimation error is higher than the pre-determined upper bound [12, 13]. In addition, this section describes normalized least-mean-square (NLMS) and set-membership NLMS (SM-NLMS) algorithm with partial update in some detail.

A. The Normalized LMS Algorithm

If one wishes to increase the convergence speed of the least-mean-square (LMS) algorithm without using estimates of the input signal, a variable convergence factor is a solution. The normalized least-mean-square (NLMS) algorithm usually converges faster than the LMS algorithm, since it utilizes a variable convergence factor.

The updating equation of the LMS algorithm can employ a variable convergence factor μ_k in order to improve the convergence rate. The updating formula is as follows

$$w(k+1) = w(k) + 2u_k e(k)x(k) = w(k) + \Delta\widetilde{w}(k) \quad (5)$$

where μ_k must be chosen with the objective of achieving a faster convergence. A method is to reduce the instantaneous squared error as possible. This method is that the instantaneous squared error is a good and simple estimate of the mean-square error (MSE).

The instantaneous squared error is given by

$$e^2(k) = d^2(k) + w^T(k)x(k)x^T(k)w(k) - 2d(k)w^T(k)x(k) \quad (6)$$

If a change given by $\widetilde{w}(k) = w(k) + \Delta\widetilde{w}(k)$ is performed in the weight vector, the corresponding to squared error can be expressed as follows

$$\begin{aligned}\widetilde{e}^2(k) &= e^2(k) + 2\Delta\widetilde{w}^T(k)x(k)x^T(k)w(k)\\ &+ \Delta\widetilde{w}^T(k)x(k)x^T(k)\Delta\widetilde{w}(k) - 2d(k)\Delta\widetilde{w}^T(K)x(k)\end{aligned} \quad (7)$$

then

$$\begin{aligned}\Delta e^2(k) &\equiv \widetilde{e}(k) - e^2(k)\\ &= -2\Delta\widetilde{w}^T(k)x(k)e(k) + \Delta\widetilde{w}^T(k)x(k)x^T(k)\Delta\widetilde{w}(k)\end{aligned} \quad (8)$$

In order of achieving a faster the convergence rate, the method is to make $\Delta e^2(k)$ negative and minimum by appropriately adjustment μ_k.

where a change given by $\Delta\widetilde{w}(k) = 2\mu_k e(k)x(k)$ in equation (8), it expressed as follows

$$\Delta e^2(k) = -4\mu_k e^2(k)x^T(k)x(k) + 4\mu_k e^2(k)\left[x^T(k)x(k)\right]^2 \quad (9)$$

The value of μ_k such that $\frac{\partial \Delta e^2(k)}{\partial \mu_k} = 0$ is expressed as

$$\mu_k = \frac{1}{2x^T(k)x(k)} \quad (10)$$

This value of μ_k led to the negative value of $\Delta e^2(k)$, thus it corresponds to a minimum point of $\Delta e^2(k)$.

Using this variable convergence factor, the updating equation for the LMS algorithm is expressed as

$$w(k+1) = w(k) + \frac{e(k)x(k)}{x^T(k)x(k)} \quad (11)$$

Usually a convergence factor μ_n is introduced in the updating formula in order to inhibit the misadjustment, since all the derivations are based on instantaneous values of the squared errors and not on the MSE. Also a parameter gamma should be included, in order to avoid large step sizes when $x^T(k)x(k)$ becomes small. The coefficient updating equation is as

$$w(k+1) = w(k) + \frac{\mu_n}{\gamma + x^T(k)x(k)} e(k)x(k) \quad (12)$$

The resulting algorithm is called the NLMS algorithm, and summarized can be represented as

Initialization

$$x(0) = \hat{w}(0) = [0 \quad 0 \quad \ldots \quad 0]^T \quad (13)$$

chose μ_n in the range $0 < \mu_n \le 2$, gamma is small constant

Do for $k \ge 0$

$$e(k) = d(k) - x^T(k)w(k) \quad (14)$$

$$w(k+1) = w(k) + \frac{\mu_n}{\gamma + x^T(k)x(k)} e(k)x(k) \quad (15)$$

The range of values of μ_n to guarantee stability can be derived by first considering that

$$E\left[x^T(k)x(k)\right] = tr[R] \quad (16)$$

and that

$$E\left[\frac{e(k)x(k)}{x^T(k)x(k)}\right] \approx \frac{E[e(k)x(k)]}{E[x^T(k)x(k)]} \quad (17)$$

That the average value of the convergence factor actually applied to the LMS direction $2e(k)x(k)$ is $\mu_n/2tr[R]$. Finally, by comparing the updating formula of the standard LMS algorithm with that of the NLMS algorithm, the desired upper bound result is $0 < \mu_n \leq 2$ or follows as

$$0 < \mu = \frac{\mu_n}{2tr[R]} < \frac{1}{tr[R]} \quad (18)$$

B. The Set-Membership NLMS Algorithm

The SMF concept is an applicable to adaptive-filtering are linear in parameters. The adaptive-filter output is given by

$$y(k) = w^T x(k) \quad (19)$$

where $x(k) = [x_0(k)x_1(k)\ldots x_N(k)]^T$ is the input signal, and $w = [w_0 \quad w_1 \quad \ldots \quad w_N]^T$ is the parameter.

Considering a desired signal sequence of $d(k)$ and a sequence of input of $x(k)$, both for $k = 0,1,2,\ldots,\infty$. The vectors $x(k)$ and $w \in R^{N+1}$, where R are real numbers, whereas $y(k)$ and $e(k)$ represent the adaptive-filter output signal and output error.

The critical idea of the SM-NLMS algorithm is to perform a test to verify if the previous estimate $w(k)$ lies outside the constraint set $H(k)$, i.e., $\left|d(k) - w^T(k)x(k)\right| > \bar{\gamma}$. If the modulus of the error signal is greater than the specified bound, the new estimate $w(k+1)$ will be updated to the closest boundary of $H(k)$ at a minimum distance, i.e., the SM-NLMS minimizes $\|w(k+1) - w(k)\|^2$ subjected to $w(k+1) \in H(k)$ [14]. The updating is performed by an orthogonal projection of the previous estimate onto the closest boundary of $H(k)$.

In order to get the update equations, first to see the a priori error $e(k)$ given by

$$e(k) = d(k) - w^T(k)x(k) \quad (20)$$

then, let's start with the NLMS algorithm which utilizes the following recursion for updating $w(k)$

$$w(k+1) = w(k) + \frac{\mu(k)}{\gamma + x^T(k)x(k)} e(k)x(k) \quad (21)$$

where in the present discussion $\mu(k)$ is the variable step size that should be appropriately chosen in order to satisfy the desired set-membership updating.

The update should the following situation

$$e(k) = d(k) - w^T(k)x(k) > \bar{\gamma} \quad (22)$$

or

$$e(k) = d(k) - w^T(k)x(k) < -\bar{\gamma} \quad (23)$$

and the a posteriori error should be given by

$$\begin{aligned} \varepsilon(k) &= d(k) - w^T(k+1)x(k) = \pm\bar{\gamma} \\ &= d(k) - w^T(k)x(k) - \frac{\mu(k)}{\gamma + x^T(k)x(k)} e(k)x^T(k)x(k) \\ &= e(k) - \frac{\mu(k)}{\gamma + x^T(k)x(k)} e(k)x^T(k)x(k) \end{aligned} \quad (24)$$

where $\varepsilon(k)$ becomes equal to $\pm\bar{\gamma}$ because the coefficients are updated to the closest boundary of $H(k)$. Since gamma, whose only task is regularization, is a small constant it can be disregarded leading to the following equality

$$\varepsilon(k) = e(k)[1 - \mu(k)] = \pm\bar{\gamma} \quad (25)$$

The above equation leads to

$$1 - \mu(k) = \pm\frac{\bar{\gamma}}{e(k)} \quad (26)$$

where the plus (+) sign applies for the case when $e(k) > 0$ and the minus (-) sign applies for the case where $e(k) < 0$. Therefore, by inspection we conclude that the variable step size, $\mu(k)$, is given by

$$\mu(k) = \begin{cases} 1 - \frac{\bar{\gamma}}{|e(k)|} & if\,|e(k)| > \bar{\gamma} \\ 0 & otherwise \end{cases} \quad (27)$$

The updating equations (20), (27), and (21) are quite similar to those of the NLMS algorithm except for the variable step size $\mu(k)$. The SM-NLMS algorithm is $y(k) = w^T x(k)$. As a rule of thumb, the value of $\bar{\gamma}$ is chose around $\sqrt{5}\sigma_n$, where

σ_n^2 is the variance of the additional noise. That the NLMS algorithm minimizes $\|w(k+1)-w(k)\|^2$ subjected to the constraintthat $w^T(k+1)x(k)=d(k)$, as such it is a particular case of the SM-NLMS algorithm by choosing the bound $\bar{\gamma}=0$. It should be noticed that by using a step size $\mu(k)=1$ in the SM-NLMS whenever $w(k)\notin H(k)$, one performs a valid update since the hyperplane with zero a posteriori error lies in H(k). In this case the resulting algorithm does not minimize the Euclidean distance $\|w(k+1)-w(k)\|^2$ since the a posteriori error is zero and less than $\bar{\gamma}$.

IV. Simulation Results

The simulation results of our adaptive filtering method are obtained to confirm the jamming rejection characteristics. The performance is expressed in terms of SNR improvement and MSPE.

(1) SNR improvement: The metric adopted to verify the steady state performance is the “SNR improvement”, which is defined in [4] and given by,

$$\mathbf{SNR}_{improvemnt} = 10\log[E|r(k)-S(k)|^2 / E|z(k)-S(k)|^2]\ (dB) \quad (28)$$

(2) Mean squared prediction error (MSPE, V_{MSPE}): The MSPE is used as an index to evaluate the convergence rate of transient responses for various algorithms. It is defined as

$$V(k)=\frac{1}{SIM_{num}}\left(\sum_{i=1}^{SIM_{num}} e_i^2(k)\right) \quad (29\text{–}1)$$

$$V_{MSPE}(n)=\log\left[\frac{1}{100}\left(\sum_{i=((n-1)*100)+1}^{n*100} V(i)\right)\right] \quad (29\text{–}2)$$

where SIMnum is the total number of simulations (which is 500 here), and $e_i(k)$ is the predicted error of the k-th iteration for the i-th run. In this simulation, the received signal is band-pass filtered. The noise power in this bandwidth can be approximated by

$$N = kT_E B \quad (30)$$

where k is Boltzmann’s constant ($1.3806\times10^{-23} JK^{-1}$), B is the bandwidth in Hz, and T_E is the effective noise temperature in Kelvin. The effective noise temperature is a function of sky noise, antenna noise temperature, line losses, receiver noise factor, and the ambient temperature. This noise power is set to be -138.5dBW [15].

The length of tapped delay line is set to ten. The converge rate μ_n is set as 0.05 and parameter gamma γ is set as 10^{-10} in the NLMS filter. The parameter γ is set as 10^{-10} and $\bar{\gamma}$ is set as 10^{-10} in the SM-NLMS filter. The next step in the process is to determine the signal power. The GPS link budget may be analyzed starting with the minimum power transmitted by the satellites. The C/A-code (1575.42MHz for carrier frequency) is transmitted at an effective level of 478.63W (26.8dBW) effective isotropic radiated power (EIRP) [16, 17]. After you know the noise power, we know that the signal is smaller than the noise, approximately is smaller than 20 dB. This results in signal power of approximately -157dBW. The above step in the process is to determine the signal power and noise power, and the next step is to add the jamming signal.

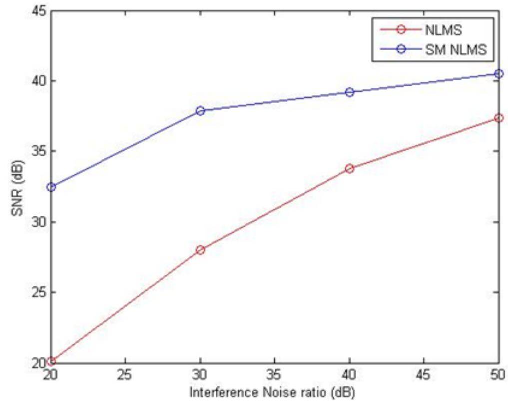
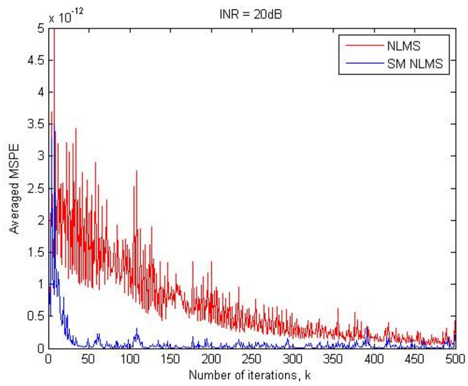


Fig. 3. Single tone continuous wave interferencesuppression performances of SNR improvement

Fig. 3 shows the interference suppression performances of SNR improvement. The INR is varied from 20dB to 50 dB. It is shown that the SM-NLMS method achieves the higher SNR improvement than the NLMS method. On average, the SM-NLMS method is 7.8 dB higher than NLMS method does.

It is shown in Figure 4 (a) to (d) that the INR is varied from 20 dB to 50 dB, respectively. The SM-NLMS method provides a better transient response and shorter convergence time than NLMS method while utilized lower computation burden. It also shows the better prediction error for SM-NLMS method under steady state condition.



(a)

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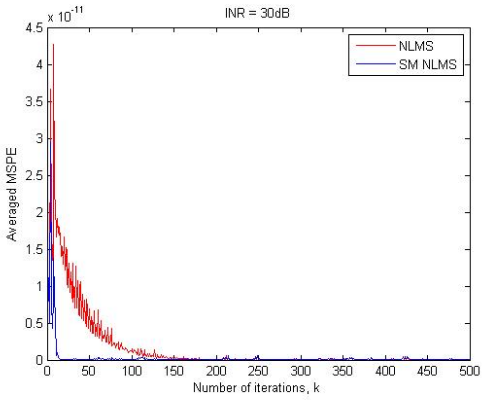

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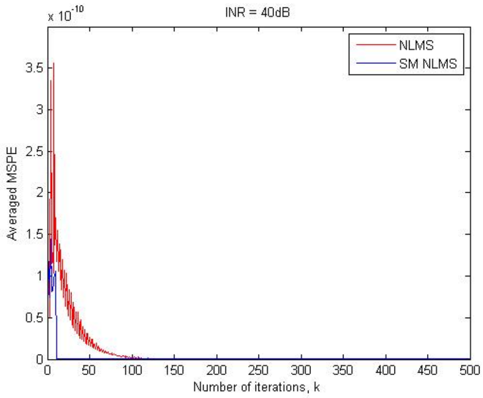
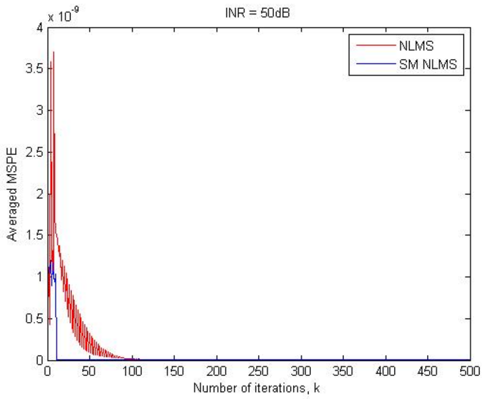


(c)



(d)

Fig. 4. jamming suppression performances of averaged MSPE (a) 20dB (b) 30dB (d) 40dB (d) 50dB.

V. CONCLUSIONS

This paper presents the adaptive filtering algorithms for GPS interference cancellation. The NLMS and SM-NLMS methods are considered for CWI jamming signal. Adjustment of the coefficients, with the prediction error of adjustment, can robustly estimate stationary jamming signals. The adaptive filtering algorithms were derived and the corresponding interference cancellation performances are presented.The proposed adaptive filtering scheme indeed achieves improved SNR and prediction error those of the adaptive filters in various INR circumstances.

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