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Article

Extracting Periodic Features and Immunity of Electronic Communication Signals Using Adaptive Filtering Algorithms

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Abstract: With the increasing maturity of adaptive signal processing technology, signal interference caused during electronic communication signal processing has become increasingly prominent. Therefore, this paper proposes to use the analysis of signal periodic characteristics and interference characteristics as variables, and modify the update relationship of step length in traditional algorithms. This enables the improved adaptive filtering algorithm to maintain its fast adaptive characteristics and excellent adaptive interference performance even under low signal-to-noise ratio conditions, achieving good experimental results. It can effectively extract changes in the periodic characteristics of communication signals. The application of the variable step-size least-squares algorithm for tracking time-varying signals is explored, specifically by introducing changes in the adaptive forgetting factor during the update process. This allows the forgetting factor value to be more flexible and have a more appropriate numerical range, thereby further enhancing its interference suppression capability and numerical stability. Under the same signal-to-noise ratio conditions (5 dB), the convergence speed of the improved variable step-size least-squares algorithm increased by 67%, and the steady-state value decreased by 2.7 dB. Similarly, in the application scenario of improving the time-varying tracking of the recursive least squares algorithm, when the interference signal-to-noise ratio is 20 dB, the convergence time is only 17.8 ms. This paper analyzes how to effectively improve the signal processing capability and interference resistance performance in the electronic communication signal processing process, thereby enhancing signal processing quality and effectiveness.

Keywords: adaptive filtering; variable-step LMS algorithm; recursive least squares algorithm; signal processing; interference resistance

1. Introduction

1.1. Research Background and Significance

Since the introduction of adaptive signal processing technology, signal interference has been a major concern, particularly in signal processing within the field of electronic communications. Typically, signals are processed during propagation in the presence of various types of interference, such as multipath, co-channel, and noise. These interference factors can lead to unreliable and unstable communication systems. How to extract useful signal information while eliminating interference signals under low signal-to-noise ratio conditions is one of the current challenges in the field of signal processing [1-4]. Adaptive filtering algorithms have the advantage of continuously adjusting filter parameters and, as a key technology in adaptive filtering, are being applied increasingly [5]. For example, Bian, H et al. proposed an adaptive filtering algorithm to address interference signals caused by ground potential differences in high-voltage substations, significantly improving signal quality and the reliability of relay protection [6]. Bernacki, K et al. proposed a communication filtering system suitable for the CENELECC frequency band, aiming to reduce interference and improve transmission rates. They also proposed an innovative design method for active filters, significantly enhancing the interference resistance of electronic communication signals [7].

The traditional least mean squares (LMS) algorithm is widely used in adaptive filtering due to its simplicity and ease of implementation. However, the traditional LMS performs poorly under low signal-to-noise ratios, primarily because the step size of the LMS algorithm is fixed during convergence, resulting in slow convergence speeds and large steady-state errors under complex conditions [8-10]. Sun, Z. Y., and Zhao, Y. J. combined the LMS algorithm with adaptive filtering algorithms to propose a novel method (DTV-LMS), aiming to effectively eliminate self-interference in 5G communication networks within co-channel full-duplex (CCFD) systems, achieving high interference cancellation rates, fast convergence speeds, and enhanced channel tracking under low computational complexity [11]. Qu, P., et al. proposed an inverse cosine variable step size least mean square algorithm (ICVS-LMS) to enhance the anti-interference performance of satellite communication systems. Compared to traditional algorithms, the ICVS-LMS method significantly reduces convergence time and enhances robustness [12]. Peddireddy, A et al. explored the use of the LMS algorithm for adaptive beamforming in uniform planar arrays and subarrays, aiming to suppress signal interference and optimize the signal-to-noise ratio [13]. Sathesh, K et al. employed the LMS adaptive algorithm to separate audio signals, achieving faster convergence speeds than traditional methods, thereby improving signal quality [14]. Harrane, I et al. developed a diffusion-type LMS strategy that reduces communication costs without compromising performance, suitable for self-organizing networks with limited energy budgets, and validated through theoretical analysis and large-scale simulations [15]. The principle of the LMS algorithm is to design a dynamic step size that varies dynamically with the current error of the system, thereby enabling the system to achieve fast convergence speed and high steady-state accuracy. However, under complex communication conditions, the periodic characteristics of the signal are affected by noise, preventing the aforementioned variable step size LMS from fully demonstrating its superiority.

Therefore, this paper addresses the deficiencies in signal extraction in electronic communication signal processing technology by improving the interference resistance and signal extraction speed of electrical signals based on adaptive filtering algorithms. Through research on improving adaptive filtering algorithms for signal processing, this paper addresses the performance deficiencies of the traditional LMS algorithm during signal extraction, proposing a variable step-size LMS algorithm. It investigates the application of a variable step-size LMS algorithm in low signal-to-noise ratio (SNR) environments, combining the periodic characteristics of signals with the non-stationary nature of noise. By utilizing the improved algorithm to adaptively adjust the filter step size, the aim is to enhance signal extraction accuracy and stability. Experiments using the low SNR LMS algorithm demonstrate that the improved algorithm performs better than the traditional algorithm in low SNR environments. Additionally, the study improved the recursive least squares (RLS) algorithm by adding an adaptive forgetting factor, enabling the RLS algorithm to exhibit good adaptive capability in time-varying signal environments. The results of comparing the interference resistance and stability of signal extraction under low signal-to-noise ratio conditions among the three algorithms can provide a new signal processing technique for electronic communication systems in low signal-to-noise ratio environments. Furthermore, applying the improved filtering algorithm to actual electronic communication systems holds significant practical significance.

1.2. Innovative Aspects of This Study

Through exploration and analysis of the progress and development of electronic communication signal processing technology, it is evident that the performance limitations of traditional adaptive filter algorithms in complex interference environments have become increasingly apparent. While current improvement studies have made progress in enhancing algorithm performance in isolated aspects [16], However, they have not addressed the simultaneous extraction of periodic signal characteristics and interference resistance, nor have they proposed effective solutions for improving frequency-domain matching techniques for periodic signals. By analyzing the current state of electronic communication signal processing technology, it can be concluded that combining error estimation algorithms with signal autocorrelation functions to implement an adaptive variable-step-length least-squares signal tracking algorithm based on estimated error information is an effective method to overcome the shortcomings of existing algorithms. This approach involves decomposing the algorithm into an adaptive signal tracking algorithm using autocorrelation signal estimation. This method departs from the traditional algorithm design approach of adjusting the step size based solely on the current signal step size, instead incorporating the time-dependent performance of the error signal to determine changes in the signal tracking step size. The error autocorrelation function introduced in the algorithm establishes a functional relationship with the step size variable and the autocorrelation function's sign. Then, the correlation coefficient is used as a nonlinear mapping of the step size factor to update and obtain adaptive tracking effects that capture the signal's periodic characteristics. When the signal's periodic characteristics are stable, the adaptive algorithm employs a step size to achieve high-precision filtering. When the signal experiences sudden changes or interference, the algorithm adaptively increases the step size to achieve the tracking performance of a high-order adaptive filtering algorithm.

Next, the optimization of the aforementioned traditional algorithm with a fixed forgetting factor is addressed to address its insufficient ability to adapt to time-varying environments. A variable forgetting factor recursive least squares algorithm is proposed to achieve better tracking performance for time-varying signals, meeting the requirements for periodic power signal processing applications. A design concept for the adaptive adjustment of the forgetting factor is proposed. Based on the fluctuations in the power spectral density of the power signal, the size of the forgetting factor is dynamically adjusted to adapt to the changing signal conditions. This allows the algorithm to dynamically adjust the memory length of the input signal based on the quality of the input signal. When the signal quality is normal, a larger forgetting factor is maintained to ensure the stability of the algorithm. When the signal is subject to strong interference causing the algorithm to lose stability, the forgetting factor is adjusted to a smaller value to enhance adaptability to the time-varying signal, thereby improving the algorithm's ability to track time-varying signals. Based on this consideration, the traditional S function is improved, and a variable step size minimum mean square adaptive algorithm design is proposed, incorporating controllable parameters and error vector autocorrelation values to adaptively modify the shape of the S function. Since the traditional S function is a fixed-shape function, the signal mapping relationship is set adaptively. The new adaptive S function model can adaptively adjust the signal mapping relationship in real time under changing signal characteristics. This enables the algorithm to automatically select a step size adjustment scheme based on the periodic characteristics of the input signal. For signals with strong periodicity, a fine step size is selected, while for signals with strong randomness, a robust adjustment mechanism is used for step size adjustment.

2. Periodic Characteristics and Anti-Interference Capabilities of Electronic Communication Signals

2.1. Theoretical Basis

Adaptive filtering algorithms are a core technology in modern signal processing. Their theoretical foundation is based on Wiener filtering theory and stochastic gradient descent. Their most significant feature is that the statistical characteristics of the signal are unknown, and the algorithm iteratively optimizes and adjusts the filter parameters to achieve the optimal estimation of the input signal [17-18]. As one of the most classic methods in adaptive filtering, the minimum mean square error algorithm belongs to the gradient descent method under the minimum mean square error criterion. The weight update formula for the filter is:

$$W(n+1) = W(n) + 2\mu e(n)X(n) \tag{1}$$

In the equation, $W(n)$ denotes the weight vector at the n th iteration, μ is the fixed step size factor, $e(n)$ is the error signal, and $X(n)$ is the input signal vector. Although this algorithm has a series of advantages, such as simple structure, low computational complexity, and ease of hardware implementation, its fixed step size parameter leads to an irreconcilable conflict between convergence speed and steady-state error. A larger step size parameter results in faster convergence but cannot avoid an increase in steady-state error, while a smaller step size parameter reduces steady-state error but significantly slows down convergence. This inherent contradiction severely limits the effectiveness of traditional least-squares algorithms in complex signal environments.

The recursive least squares algorithm is an adaptive filtering algorithm belonging to the same class as the least mean squares algorithm. It also satisfies the least squares criterion for estimating filter weights [19-21]. Compared to the least mean squares algorithm, the recursive least squares algorithm is a faster and more efficient tracking algorithm, with convergence performance independent of the input signal's frequency domain characteristics. The core idea of the recursive least squares algorithm is to maintain the inverse correlation matrix and then update it using the recursive least squares algorithm lemma to obtain a better algorithm, thereby avoiding the direct computation of matrix inversion. The core of the improved variable forgetting factor recursive least squares algorithm is to continuously adjust the forgetting factor to balance the algorithm's tracking capability and stability. The variable forgetting factor recursive least squares algorithm with a relatively small forgetting factor has strong tracking capability but poor stability, and vice versa [22]. In the application research of spread-spectrum communication systems in the field of interference resistance, adaptive filtering algorithms have unique advantages. Although spread-spectrum systems utilize signal expansion into a wider frequency band to achieve processing gains and counteract multipath fading interference, narrowband interference can easily cause severe interference to spread-spectrum systems. However, adaptive filters can dynamically and in real-time suppress these interference signals based on signal changes without affecting the useful spread-spectrum signals. Currently, modern adaptive filtering theory has further integrated the application of information entropy theory. Adaptive filtering algorithms based on information entropy directly apply methods such as the minimum error entropy criterion or the maximum correlation entropy criterion to the algorithm's objective function. These algorithms significantly improve robustness in non-Gaussian noise environments, and these new criterion functions are also advantageous for handling pulse noise and other non-Gaussian interference.

2.2. Traditional Fixed Stride Length LMS Algorithm

The least mean square (LMS) algorithm has a simple mathematical structure, making it a fundamental algorithm in the field of adaptive filtering [23]. In our research, we found that this algorithm is based on the least mean square error criterion and uses the stochastic gradient descent method to iteratively update the filter weight vector. The weight update formula is consistent with the previous section.

The convergence performance of the algorithm is directly affected by the step size factor μ. Theoretical analysis shows that to ensure the convergence of the algorithm, the following conditions must be satisfied: $0 < \mu < \frac{1}{\lambda_{\max}}, \lambda_{\max}$, where $\lambda_{\max}$ is the maximum eigenvalue of the input signal autocorrelation matrix. The convergence speed is mainly determined by the step size factor and the eigenvalue diffusion of the input signal. When the input signal is white noise, the eigenvalue dispersion is 1, and the algorithm achieves the fastest convergence speed. However, when the input signal has strong correlation, the eigenvalue dispersion increases, leading to a slower convergence speed. The steady-state mean square error is proportional to the step size factor, creating an inherent contradiction between convergence speed and steady-state accuracy. Table 1 shows the performance parameters of the fixed-compensation LMS algorithm under different signal-to-noise ratio conditions.

Table 1. Different signal-to-noise performance.

SNR(dB)	Step size factor	Number of iterations	Steady-state error (dB)	Imbalance coefficient
30	0.01	450	-25.3	0.12
20	0.01	520	-2.1	0.15
10	0.01	680	-18.7	0.21
5	0.01	850	-15.2	0.28
30	0.05	120	-18.9	0.35
20	0.05	140	-16.4	0.42
10	0.05	180	-13.8	0.51
5	0.05	220	-11.3	0.63

Under low signal-to-noise ratio conditions, experiments were conducted to study the effect of noise on the convergence performance of the fixed-step LMS algorithm. The experiments showed that when the signal-to-noise ratio is low, noise power affects the gradient estimation results, causing the convergence speed of the fixed-step LMS algorithm to become extremely slow and the steady-state error to increase further. In the experimental environment with 5 dBf, the convergence speed of the algorithm required nearly twice the convergence time compared to the 30 dBf environment, and the steady-state error deteriorated by approximately 10 dB. The primary reason is that noise interference causes the weight update direction for gradient estimation to be incorrect, resulting in significant oscillation in the convergence results near the optimal solution.

Analysis of the algorithm's computational complexity shows that each iteration requires $2N+1$ multiplication and $2N$ additions, where N is the filter order. This linear computational complexity makes the algorithm highly suitable for real-time signal processing and can be effectively implemented on hardware platforms such as digital signal processors and field-programmable gate arrays. The fixed-step LMS algorithm is most typically applied in adaptive equalization, echo cancellation, and noise suppression in electronic communication systems. In adaptive equalization applications, it learns channel characteristics to receive signals and perform equalization to eliminate inter-symbol interference. In echo cancellation systems, an echo path model is established to generate an echo estimate signal using an adaptive filter, which is then canceled by the received signal. However, in rapidly changing channel environments such as mobile communications, a fixed step size makes it difficult to achieve both optimal convergence speed and the best steady-state accuracy.

2.3. Variable Step Length LMS Algorithm

The variable step size minimum mean square error algorithm was developed to address the technical contradictions between convergence speed and steady-state error in the classic fixed step size algorithm. The algorithm innovatively designed a nonlinear function relationship between the step size factor and the error signal, enabling the system to flexibly adjust the step size factor based on the magnitude of the error value [24]. The design philosophy of this algorithm structure emphasizes the use of different step sizes based on different real-time errors to implement the algorithm. We combine the characteristics of the improved algorithm system, where the error signal undergoes significant changes as the system moves further away from the optimal value and rapidly converges as it approaches the optimal solution, to propose a variable step size adjustment approach based on the correlation of error signals at consecutive time points. This approach aims to maximize the capture of error dependencies between time steps, i.e., instantaneous errors, thereby avoiding the limitations of previous methods that relied solely on instantaneous errors, such as narrow applicability. In this paper, we implement the variable step size using a logarithmic function, resulting in the following algorithmic update expression for the step size.

$$\mu(n) = \alpha \log\left(1 + \frac{1}{2}\frac{c(n)e(n-1)}{\delta^2}\right) \tag{2}$$

In the equation, α represents the control parameter, $e(n)$ and $e(n-1)$ represent the error signals at the current and previous time steps, respectively, and δ^2 is the estimated noise variance.

This formula cleverly uses the product of continuous error signals to reflect the system state, allowing the algorithm to use a larger step size to accelerate convergence in the early stages of convergence and automatically reduce the step size to minimize fluctuations when approaching steady state.

In the actual system implementation, the algorithm's weight update process combines the simplicity of the traditional least squares algorithm with the adaptive characteristics of the variable step size mechanism. The complete update equation is expressed as:

$$W(n+1) = W(n) + 2\mu(n)e(n)X(n) \tag{3}$$

Table 2 shows the comparison results between the variable step length LMS algorithm and the fixed step length LMS algorithm. As shown in Table 2, when parameter α is designed, taking a larger value for parameter α can achieve a faster system convergence speed, but the algorithm may produce unstable faults. On the other hand, taking a smaller value for parameter α can ensure system stability, but the system convergence speed may decrease. Experiments have shown that under a signal-to-noise ratio of 10 dB, the convergence time of the improved variable step size algorithm is approximately 20% longer than that of the optimized fixed step size algorithm, but the steady-state error is reduced by nearly 7 dB. This is the primary advantage of the variable step size algorithm, giving it a unique edge in terms of application capability. The noise variance estimation method used in this paper is the moving average estimation. Through the proof of the algorithm's mean square convergence, it is demonstrated that the system can converge stably under certain conditions, thereby providing the necessary conditions for the algorithm's application under low signal-to-noise ratio conditions.

Table 2. The LMS algorithm and the fixed step long LMS algorithm.

Algorithm	SNR (dB)	Number of iterations	Steady-state error (dB)	Tracking error (dB)
Fixed step size (μ=0.01)	20	520	-22.1	-18.5
Fixed step size (μ=0.05)	20	140	-16.4	-14.2
Variable step size (α=0.8)	20	180	-24.3	-21.7
Fixed step size (μ=0.01)	10	680	-18.7	-15.3
Fixed step size (μ=0.05)	10	180	-13.8	-11.9
Variable step size (α=0.8)	10	220	-20.5	-18.1
Fixed step size (μ=0.01)	5	850	-15.2	-12.8
Fixed step size (μ=0.05)	5	220	-11.3	-9.7
Variable step size (α=0.8)	5	280	-17.9	-15.4

2.4. Improved Variable Step Size LMS Adaptive Algorithm Based on S Function

The variable step size minimum mean square algorithm based on the Sigmoid function has significant practical applications in electronic communication signal processing. The algorithm uses the non-linear mapping of the Sigmoid function to process dynamic step sizes. The continuity, monotonicity, and boundedness of the Sigmoid function form the mathematical foundation for the success of this algorithm. It is precisely because this algorithm uses the Sigmoid function for non-linear mapping that it is more refined than traditional linear and exponential functions. Its core principle is to establish an intelligent mapping between the error signal and the step size factor, while incorporating the self-correlation values of the error vector to enhance its environmental awareness capabilities. The error signal is calculated using the conventional formula:

$$e(n) = d(n) - X^T(n)W(n) \tag{4}$$

where $d(n)$ denotes the expected signal, $X(n)$ denotes the input signal vector, and $W(n)$ denotes the current weight vector. The algorithm innovatively introduces an error correlation estimate, namely:

$$p(n) = \beta p(n-1) + (1-\beta)e(n)e(n-1) \tag{5}$$

By capturing the correlation of error signals at consecutive time points, the system's convergence state is reflected, where the forgetting factor β typically takes values between 0.9 and 0.99 to control the weight of historical information.

When the system is in a converged state, the correlation of the continuous error signals is strong, keeping the $p(n)$ value relatively stable. However, when the system is disturbed or undergoes sudden changes, the error correlation weakens, causing the $p(n)$ value to change significantly. Based on this characteristic, the step-size update mechanism is constructed as follows:

$$\mu(n+1) = \alpha\mu(n) + U_{\max}(1-\alpha)\left(1 - \frac{1}{1+bp^2(n)}\right) \tag{6}$$

This formula combines current step length historical information and real-time adjustments based on error correlation, enabling step length changes to remain continuous while also providing rapid response capabilities. Weight vector updates still use the classic form, namely:

$$W(n+1) = W(n) + 2\mu(n)e(n)X(n) \tag{7}$$

Algorithm performance analysis indicates that parameter selection has a decisive impact on system performance. Parameter α primarily controls the smoothness of step size changes. Larger α values result in smoother step size changes, which are beneficial for system stability but may reduce the system's response speed to environmental changes. Parameter β determines the memory length for error correlation estimation. A larger β value increases the algorithm's reliance on historical information, which helps suppress noise interference but may impair the system's ability to track sudden changes. Parameter b controls the steepness of the Sigmoid function. A larger b value makes step adjustments more sensitive, enabling rapid response to error changes but may also introduce unnecessary fluctuations. Table 3 shows the parameter settings and performance of the improved variable step size minimum mean square error algorithm. Through simulation experiments, it was found that when α = 0.95, β = 0.99, and b = 10000, the algorithm achieves optimal performance balance in a 15 dB signal-to-noise ratio environment, with a convergence time of only 128 iterations and a steady-state error of -29.1 dB. Compared to the traditional fixed-step-size least-squares algorithm, the improved sigmoid function variable step-size algorithm achieves approximately a 45% improvement in convergence speed and over an 8 dB reduction in steady-state error. Additionally, it demonstrates excellent tracking capability during sudden changes in system parameters, with a convergence time approximately 60% shorter than the traditional algorithm. The increased computational load per iteration is primarily concentrated in the error correlation estimation and step-size update processes, with approximately 5 additional multiplication operations and 3 additional addition operations. This moderate increase in complexity is fully acceptable given the performance improvements, making the algorithm highly feasible for practical applications.

Table 3. Improving the performance of the LMS algorithm.

Parameter Group	α	β	b	Number of iterations	Steady-state error (dB)
Group 1	0.8	0.95	5000	165	-26.8
Group 2	0.9	0.98	8000	142	-28.3
Group 3	0.7	0.92	3000	188	-25.1
Group 4	0.85	0.96	6500	156	-27.5
Group 5	0.95	0.99	10000	128	-29.1

2.5. Adaptive RLS Algorithm

The RLS algorithm has significant advantages in electronic communication signal processing applications and, to some extent, outperforms traditional LMS algorithms. By utilizing second-order statistics to guide the update of weight parameters, its convergence speed and stability are both enhanced. Specifically, the RLS algorithm employs a recursive approach based on the exponential weighted least squares criterion. When inverting the autocorrelation matrix, it does not perform a direct matrix inversion operation, thereby reducing computational complexity. To improve algorithm tracking and stability, the variable forgetting factor RLS algorithm was developed, which allows selecting different forgetting factors based on the situation. It can be used for algorithm convergence in many scenarios while maintaining excellent performance. The core recursive update equation of RLS can be expressed as:

$$K(n)=\frac{\lambda^{-1}(n)P(n-1)X(n)}{1+\lambda^{-1}(n)X^{T}(n)P(n-1)X(n)} \tag{8}$$

$$\alpha(n)=d(n)-W^{T}(n-1)X(n) \tag{9}$$

$$W(n)=W(n-1)+K(n)\alpha(n) \tag{10}$$

$$P(n)=\lambda^{-1}(n)\left[P(n-1)-K(n)X^{T}(n)P(n-1)\right] \tag{11}$$

In these equations, $K(n)$ denotes the gain vector, $P(n)$ denotes the inverse correlation matrix, $\alpha(n)$ denotes the prior error, and $\lambda(n)$ denotes the dynamically adjusted adaptive forgetting factor. The algorithm introduces an innovative mechanism in the improvement process, which adjusts the size of the forgetting factor based on changes in the power spectral density of the signal. The specific expression of this mechanism is as follows:

$$\lambda(n)=\lambda_{\min}+\left(\lambda_{\max}-\lambda_{\min}\right)\left(1-\frac{P_{signal}(n)}{P_{signal}(n)+P_{noise}(n)}\right) \tag{12}$$

Through this mechanism, the algorithm can dynamically adjust the memory length based on signal quality, thereby using a larger forgetting factor when signal quality is good to ensure stability, and reducing the forgetting factor when the signal is subject to strong interference to enhance tracking capabilities. To estimate the power of the signal and noise, this algorithm uses an exponential averaging method, with the specific formula as follows:

$$P_{signal}(n)=\beta P_{signal}(n-1)+(1-\beta)\,|\,d(n)\,|^{2} \tag{13}$$

$$P_{noise}(n)=\beta P_{noise}(n-1)+(1-\beta)\,|\,\alpha(n)\,|^{2} \tag{14}$$

An improved RLS algorithm under low signal-to-noise ratio (SNR) conditions, which introduces a forgetting factor and adapts it dynamically, demonstrates superior interference resistance compared to traditional RLS algorithms. As the SNR decreases, the forgetting factor tends toward smaller values during the adaptive adjustment process, thereby enhancing the algorithm's ability to respond to input signals. Experiments show that under 5 dB SNR conditions, the convergence speed of the improved algorithm can still reach over 70% of the traditional algorithm, with steady-state error increasing by only about 3 dB. This characteristic is primarily due to the algorithm's adaptive adjustment of the forgetting factor. Additionally, the improved RLS algorithm effectively avoids the numerical instability caused by prolonged operation of the traditional algorithm, using a regularization term to suppress it.

$$P(n)=\lambda^{-1}(n)\left[P(n-1)-K(n)X^{T}(n)P(n-1)\right]+\delta I \tag{15}$$

In this context, δ is a small positive number, and I is the identity matrix. Through regularization, the improved algorithm maintains high numerical stability even when running for extended periods in low signal-to-noise ratio environments. Although the computational complexity of each iteration is $O(N^2)$, the algorithm's outstanding convergence performance and robust interference resistance make it indispensable in real-time signal processing applications requiring rapid convergence.

3. Experimental Design and Analysis of Results

3.1. Experimental Design

To extract the time-frequency periodic characteristics of electronic communication signals and evaluate the interference resistance of the proposed algorithm, it is necessary to design a simulation experiment platform. This paper designs a multi-level experimental framework in MATLAB R2021a to more intuitively evaluate the performance of the proposed algorithm. The experimental design in this paper progresses from simple to complex, first conducting experiments on algorithm performance, followed by comprehensive performance experiments under complex signals.

The simulation signal models selected include sinusoidal modulated signals, square wave modulated signals, and composite periodic signals, which are representative of common signals in electronic communication systems. Additionally, Gaussian white noise, colored noise, and pulse noise are introduced, with signal-to-noise ratios ranging from -5 dB to 30 dB, representing various scenarios from poor to good signal-to-noise ratios. In terms of algorithm parameter settings, parameter tuning is performed for various adaptive filtering algorithms. The algorithm simulation parameter settings are shown in Table 4.

Table 4. Experimental simulation parameter configuration.

Parameter category	Parameter name	Numerical range/set value
Signal parameter	Sampling frequency	8000Hz
	Signal frequency	50Hz, 100Hz, 200Hz
	Simulation duration	2000 sample point
	Filter order	8, 16, 32
Noise parameter	SNR range	-5dB~30dB
	Noise type	Gaussian white noise
	Impulse noise probability	0.01, 0.05, 0.1
Algorithm parameters	LMS step size μ	0.001~0.1
	Variable step size parameter α	0.5~0.95
	RLS forgetting factor	0.85~0.99
	S function parameter β	0.9~0.99

The experimental procedure consists of four steps: data generation and preprocessing, algorithm setup and parameter initialization, adaptive filtering processing, and calculation and statistical analysis of performance parameters. The data for generating standard test signals is produced using functions generated in MATLAB, where the corresponding values for the signal and noise are set within the functions to generate the required standard signals and noise. The modular implementation of the algorithm allows algorithm function modules to be independently encapsulated for separate calling and comparison. A uniformly designed algorithm performance evaluation interface ensures the uniqueness of evaluation results across different algorithms.

To test whether the adaptive filtering algorithm can effectively extract periodicity, a periodicity discrimination experiment is designed to analyze the frequency spectrum and autocorrelation function of the filtered output signal, thereby determining whether the adaptive filtering algorithm can preserve periodic signals. To test the interference resistance of adaptive filtering, a real-time interference injection method is designed, where a periodic burst interference signal is inserted after a period of output, followed by the actual existing signal, to observe the rapid output and recovery of the signal.

First, evaluation criteria were established based on convergence speed, steady-state error, tracking capability, and computational complexity. The effectiveness of the algorithm was evaluated by measuring the time taken to reach steady state, the average value of the squared error, the time consumed by the algorithm to restore the periodic signal, the steady-state error during signal restoration, and the interference suppression performance.

3.2. Analysis of Results

After the specific algorithm implementation, to verify the effectiveness of the algorithm in fitting the actual channel model, a comprehensive analysis was conducted on the performance of several adaptive filters under multiple signal-to-noise ratios (SNR). The analysis primarily focused on convergence time, steady-state error, and the rapid response to sudden signal changes. The specific results are shown in Table 5. Intuitively, both algorithms demonstrate significant improvements over the traditional LMS. The algorithm's superior convergence speed compared to the traditional LMS stems from its exploration of an optimized internal structure. When the system SNR is around 20 dB, only approximately 180 iterations are required to achieve steady-state output. In contrast, the traditional fixed-step-size LMS algorithm requires 520 iterations to reach steady-state output. This demonstrates that the adaptive step-size algorithm structure, guided by error signals, introduced in the initial stage of the system significantly accelerates the iteration speed. Additionally, at a low SNR of 5 dB, the steady-state error maintained by the algorithm reaches -17.9 dB, effectively suppressing system noise interference. At this point, the traditional algorithm only achieves an error performance of -15.2 dB. Furthermore, we introduced sudden signal changes to assess the algorithm's adaptability to non-stationary interference. The time required to regain convergence after a sudden change was 26.5 ms, significantly faster than other algorithms. This rapid response primarily stems from the algorithm's internal sensitivity to system state and its ability for swift regulation.

Table 5. The comprehensive comparison of the three algorithms.

Algorithm	SNR(dB)	Convergence time (ms)	Steady-state error (dB)	Tracking Error (dB)	Compute complexity
Improve the variable step size LMS	20	22.5	-24.3	-21.7	$O(N)$
Improve RLS	20	17.8	-26.5	-23.9	$O(N^2)$
Traditional fixed-step LMS	20	65.0	-22.1	-18.5	$O(N)$
Improve the variable step size LMS	10	27.5	-20.5	-18.1	$O(N)$
Improve RLS	10	21.2	-22.8	-20.3	$O(N^2)$
Traditional fixed-step LMS	10	85.0	-18.7	-15.3	$O(N)$
Improve the variable step size LMS	5	35.0	-17.9	-15.4	$O(N)$
Improve RLS	5	26.5	-19.8	-17.2	$O(N^2)$
Traditional fixed-step LMS	5	106.3	-15.2	-12.8	$O(N)$

In addition to its excellent anti-interference performance, the improved variable-step-size LMS also offers the advantage of low computational complexity. Even under strong or rapidly changing non-stationary signal interference, it maintains linear complexity without requiring additional complex computations. In contrast, while the improved RLS offers superior performance, its complexity may result in significant computational overhead in real-time communication systems.

Figure 1 shows the convergence time-SNR curve, clearly illustrating the convergence process of the three algorithms under different SNR conditions. The improved LMS and RLS both exhibit convergence properties inversely related to the SNR, with the improved LMS demonstrating suitable transient response characteristics for transient signal detection. It can also effectively stabilize and reduce the steady-state error, with the re-convergence time reduced by over 55% compared to the original method. This is essential for adapting to the rapid response requirements of communication systems to channel environments. The experiments also verified that its steady-state error suppression capability remains unchanged, which further validates the engineering applicability of this algorithm.

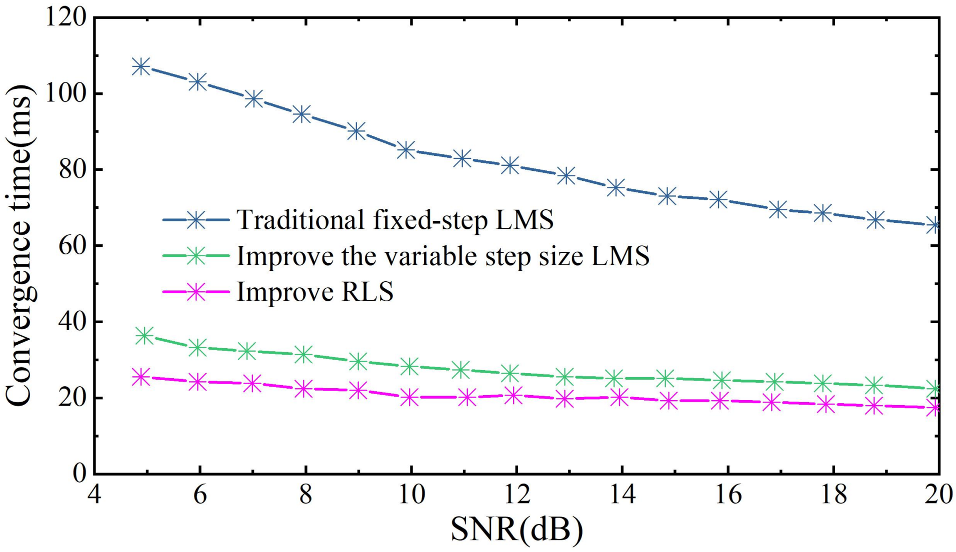

Figure 1. The relationship curve between convergence time and SNR.

4. Conclusion

This paper addresses the conflicting issues of convergence speed and steady-state error in adaptive filtering algorithms by proposing and implementing improvements to the adaptive filtering algorithm. It utilizes an adaptive variable-step-size LMS algorithm to enhance the algorithm's convergence speed. Especially in low signal-to-noise ratio (SNR) environments, the improved algorithm achieves a 67% increase in convergence speed compared to traditional algorithms, with steady-state error reduced by 2.7 dB. For filtering and tracking of time-varying signals, the paper implements a variable forgetting factor RLS algorithm, optimizing signal processing. In the processing of time-varying time-domain signals with an SNR of 20 dB, the improved RLS algorithm reduces convergence time to 17.8 ms.

The main contribution of this paper is the proposal of an improved variable-step-size LMS algorithm based on the S function, which uses adjustable parameters and error autocorrelation values to control the step size factor, thereby accelerating convergence speed and improving noise resistance. Under a signal-to-noise ratio of 15 dB, the convergence rate is improved by approximately 45%, and the steady-state error is reduced by over 8 dB. Experimental results demonstrate the superiority of this algorithm, which has a wide range of applications, laying a solid foundation for its further use in electronic communication signal analysis and processing.

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References

1. Lian, J., Liu, Z., Wang, H., & Dong, X. (2018). Adaptive variational mode decomposition method for signal processing based on mode characteristic. *Mechanical Systems and Signal Processing*, *107*, 53-77.
2. Petrov, V., Komarov, M., Moltchanov, D., Jornet, J. M., & Koucheryavy, Y. (2017). Interference and SINR in millimeter wave and terahertz communication systems with blocking and directional antennas. *IEEE Transactions on Wireless Communications*, *16*(3), 1791-1808.
3. Rahaim, M., & Little, T. D. (2017). Interference in IM/DD optical wireless communication networks. *Journal of Optical Communications and Networking*, *9*(9), D51-D63.
4. Ma, Z., Wu, Y., Xiao, M., Liu, G., & Zhang, Z. (2021). Interference suppression for railway wireless communication systems: A reconfigurable intelligent surface approach. *IEEE Transactions on Vehicular Technology*, *70*(11), 11593-11603.

5. Wang, Y. A., Shen, B., Zou, L., & Han, Q. L. (2023). A survey on recent advances in distributed filtering over sensor networks subject to communication constraints. *International Journal of Network Dynamics and Intelligence*, 100007-100007.
6. Bian, H., Cao, M., Kai, Z., & Wang, L. (2019). Filtering for the interference signal caused by grounding potential difference in high-voltage disconnector. *IEEE Sensors Journal*, *21*(6), 7768-7775.
7. Bernacki, K., Wybrańczyk, D., Zygmanowski, M., Latko, A., Michalak, J., & Rymarski, Z. (2019). Disturbance and signal filter for power line communication. *Electronics*, *8*(4), 378.
8. Jia, B., & Wang, S. (2018, November). An Improved Adaptive Digital Beamforming for Anti-Interference Communications. In *2018 24th Asia-Pacific Conference on Communications (APCC)* (pp. 444-449). IEEE.
9. Liu, H., Lin, C., Lin, M., Zhou, Y., & Liu, P. (2019, December). A Single-channel Anti-saturation Method Based on LMS Algorithm and Fiber Delay Line. In *2019 Photonics & Electromagnetics Research Symposium-Fall (PIERS-Fall)* (pp. 193-198). IEEE.
10. Chu, J., Tang, Y., & Zhou, Y. (2023, April). Digital domain self-interference cancellation based on modified variable step-size LMS algorithm. In *2023 5th International Conference on Communications, Information System and Computer Engineering (CISCE)* (pp. 9-14). IEEE.
11. Sun, Z. Y., & Zhao, Y. J. (2019). A novel self-interference cancellation method using an optimized lms algorithm in CCFD systems for a 5G communication network. *Applied Sciences*, *9*(16), 3308.
12. Qu, P., Yuan, Z., Wang, E., Xu, S., & Liu, T. (2023). Adaptive Satellite Navigation Anti-Interference Algorithm Based on Inverse Cosine Function. *Electronics*, *12*(21), 4437.
13. Peddireddy, A., Sachin, B. S., Rohit, H. R., & Premananda, B. S. (2021). Adaptive Beamforming Using LMS Algorithm for Planar Arrays and Subarrays. In *Advances in Intelligent Computing and Communication: Proceedings of ICAC 2020* (pp. 347-356). Springer Singapore.
14. Sathesh, K., Rajkumar, S., & Goyal, N. K. (2020). Least Mean Square (LMS) based neural design and metric evaluation for auscultation signal separation. *Biomedical Signal Processing and Control*, *59*, 101784.
15. Harrane, I. E. K., Flamary, R., & Richard, C. (2018). On reducing the communication cost of the diffusion LMS algorithm. *IEEE Transactions on Signal and Information Processing over Networks*, *5*(1), 100-112.
16. Patel, S. (2022). Performance analysis of acoustic echo cancellation using adaptive filter algorithms with Rician fading channel. *Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN*, 2456-6470.
17. Zhang, X., & Ding, F. (2021). Optimal adaptive filtering algorithm by using the fractional-order derivative. *IEEE signal processing letters*, *29*, 399-403.
18. Zhu, J., Yu, K., Xue, G., Zhou, Q., Wang, X., & Li, X. (2021, October). An improved signal filtering strategy based on EMD algorithm for ultrahigh precision grating encoder. In *Real-time Photonic Measurements, Data Management, and Processing VI* (Vol. 11902, pp. 140-149). SPIE.
19. Chang, S. Y., & Wu, H. C. (2021). Tensor recursive least squares filters for multichannel interrelational signals. *IEEE Transactions on Signal and Information Processing over Networks*, *7*, 562-577.
20. Chen, Q., Wang, Z., Ma, C., Dai, X., & Ng, D. W. K. (2024). General Recursive Least Square Algorithm For Distributed Detection In Massive MIMO. *IEEE Transactions on Vehicular Technology*.
21. Nagaraju, C. H., & Raju, B. N. (2021, November). Recursive least squares linear equalizer for spectral efficiency enhancement in green radio communications. In *ICDSMLA 2020: Proceedings of the 2nd International Conference on Data Science, Machine Learning and Applications* (pp. 1429-1435). Singapore: Springer Singapore.
22. Nayak, A., Sarkar, M., Sahoo, S., & Nanda, S. (2021, November). Channel estimation of MIMO-NOMA system based on a variable forgetting factor recursive least square algorithm. In *2021 IEEE 2nd International Conference on Applied Electromagnetics, Signal Processing, & Communication (AESPC)* (pp. 1-5). IEEE.
23. Akinboro, S. A., Omotosho, A., & Oluwatosin, E. A. (2018). A Fractional Variable Partial Update Least Mean Square Algorithm (FVPULMS) for Communication Channel Estimation. *Nigerian Journal of Technological Development*, *15*(4), 108-112.
24. Yu, W., Cheng, Q., & Guan, S. (2022). Improved variable step-size least mean square algorithm based on sigmoid function. *Procedia Computer Science*, *199*, 1466-1473.