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A method for noise reduction and accuracy improvement of sensor signals based on adaptive filtering

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Abstract This paper proposes a noise suppression method based on an improved LMS adaptive filtering algorithm. Signal processing system software is designed to utilize the LMS adaptive filtering algorithm in a digital signal processor (DSP) to filter the acquired voltage signals. After noise reduction, the signals are converted into digital signals and then output as corresponding graphics or waveforms. The genetic algorithm is used to optimize the LMS variable step size parameters, addressing the contradiction between the convergence speed and steady-state error of traditional fixed step size algorithms, thereby enhancing signal processing capabilities. Research indicates that the signal level ranges for the low-frequency and high-frequency channels after LMS adaptive filtering decomposition are [-6.516, 6.731] and [-2.991, 1.925], respectively. When the step size factor is set to 1/500, the signal denoising accuracy is higher. When the threshold function is set to a soft function and the number of filtering decomposition layers is set to 4, only one singular value occurs, and the denoising effect is better.

Index Terms DSP, LMS adaptive filtering, genetic algorithm, variable step size parameter optimization, signal denoising

I. Introduction

With the rapid development of the sensor industry, an increasing number of people are using high-precision sensors to collect data. Through the use of high-performance sensors and signal processing technology, accurate and reliable information can be obtained from detected signals [1]-[3]. A sensor is a measurement component or device that converts a measured quantity (such as position, force, acceleration, etc.) into a physical quantity (such as electrical quantity) with a definite correspondence, which is easy to process and measure with a certain degree of precision [4]. Sensors play a crucial role in detection systems, as their performance directly impacts the overall measurement accuracy and sensitivity of the system. If the sensor has significant errors, even if subsequent measurement components (such as circuits, human bodies, plants, materials, natural phenomena, etc.) and amplifiers have high precision, it will be difficult to improve the overall system accuracy [5]-[8]. As the frontline sentinel of an automatic control system, a sensor functions like an electronic eye, receiving and converting measured information into effective electrical signals. However, some useless signals are also mixed in, collectively referred to as noise [9]-[11]. The output impedance of sensors is generally very high, causing significant attenuation of the output signal, and sensors are easily overwhelmed by noise signals [12], [13]. Therefore, the presence of noise inevitably affects the accuracy and resolution of sensors, and since sensors are the first step in detecting automatic control systems, this inevitably impacts the performance of the entire automatic control system. Thus, noise research is an essential consideration in sensor design. Only by effectively suppressing and reducing the impact of noise can sensors be utilized effectively, thereby improving the resolution and accuracy of the application system [14]-[16].

However, noise comes in various types with complex causes, and its interference capabilities vary significantly, leading to different noise suppression methods. Literature [17] developed a probabilistic undirected graph model and applied it to noise reduction in the output of dynamic visual sensors under the optimization of an iterative conditional mode algorithm. This method not only eliminates noise but also improves the recognition accuracy of address-event representation data. Reference [18] proposes a multi-modal wearable biosensor noise reduction method for respiratory and external noise, guided by noise reference signals from photoplethysmography and combined with machine learning models, achieving higher performance and reliability compared to the baseline model. Reference [19] establishes a two-stage convolutional neural network model based on multiple multi-directional feature extraction blocks, which removes sensor noise from phase-locked thermal imaging by extracting local features in different directions and removes background interference from imaging by extracting global features. Reference [20] designed a pulse interval compensation algorithm to separate high-frequency noise from the pulse intervals of high-speed pulsed image sensors and compensate for it in the corresponding pulse intervals. By comparing the compensated data with the original data, noise in the image sensor can be effectively removed. Reference [21] addresses multi-modal joint pulse eddy current signal sensors. Based on the induction interference mechanism, it constructs an improved noise reduction method combining whale optimization, variational modal decomposition, singular value decomposition, and wavelet threshold denoising hierarchical processing, which aids in signal feature extraction and improves the detection accuracy of pulse eddy current signals. Reference [22] decomposed the signal from an impact-type sunflower yield sensor using complementary set empirical mode decomposition with adaptive decomposition capabilities, and introduced wavelet threshold denoising to process high-frequency noise, obtaining denoised sensor signals in the reconstruction process. Reference [23] integrates full set empirical mode decomposition, adaptive noise, multi-scale arrangement entropy structure, and interval thresholding to establish a distributed acoustic sensor signal denoising method, which has been proven to be effective and reliable in practice.

Filtering is an important means of removing noise and plays a significant role in sensor signal noise removal. Reference [24] employs a method supported by rate distribution spatial filtering to reduce battery consumption and noise in wireless acoustic sensor networks. Reference [25] investigates an inverse kernel non-local mean denoising algorithm for high-resolution displacement sensor image signals. This algorithm not only reduces image noise and improves sensor accuracy but also enables nanometer-level positioning measurements. Reference [26] utilized a complementary filter to address noise issues in tilt sensors within the balance system of humanoid robots. Experimental tests validated the filter's effectiveness, and its output data aided the robot in executing balance maneuvers. Reference [27] shared a nonlinear filter-based CycleGAN framework for sensor signal denoising, which achieved a better signal-to-noise ratio compared to wavelet thresholding and improved the accuracy of tool wear detection. Reference [28] employs the Kalman filter algorithm to effectively suppress vibration noise in displacement sensors, and this algorithm can accurately establish the correlation between resistance changes and sensor displacement. Reference [29] designs a Kalman filter equation that effectively reduces noise in inertial measurement unit sensor readings, particularly in scenarios with extreme data and noise frequencies that interfere with useful signals. Reference [30] applies the least squares method to fit temperature sensor data and remove nonlinear factors, tracks noise evolution in real time and calculates noise variance under the wavelet transform method, and combines wavelet transform and Kalman smoothing filtering for sensor noise reduction, achieving better accuracy and stability than single Kalman filtering.

Adaptive filtering utilizes the filter parameters and error signals obtained from the previous time step to automatically adjust the current filter parameters according to a “criterion” to adapt to the unknown or time-varying statistical characteristics of the signal and noise, thereby achieving optimal filtering. It plays an extremely important role in fields such as radar, sonar, image processing, computer vision, seismic exploration, biomedicine, and communications [31]-[34]. Since Widrow, B proposed the theory of adaptive filtering in 1967, this filtering method has gained widespread attention because it can automatically adjust parameters through self-learning to adapt to changes in the external environment and achieve optimal performance [35]. It combines the optimal filtering performance of Wiener filtering and Kalman filtering but does not require any prior statistical knowledge about the signal and noise, enabling effective noise removal [36], [37]. Reference [38] developed an adaptive wavelet filter for image denoising, applying variable stripe denoising to remote sensing image data under a representation of weights and variance parameters based on digital value probabilities. Combined with an edge compensation method, it reduces the adaptability of stripe noise, achieving denoising of remote sensing images for different observation targets. Reference [39] constructed an adaptive weighted distributed filtering algorithm based on adaptive filtering algorithms, which can effectively reduce signal noise interference in wireless sensor networks within a certain range, enhance network signals, and improve accuracy.

This paper utilizes the integrated development environment Code Composer Studio to develop signal processing system software, establish the software architecture and specific operational procedures, and achieve real-time monitoring. The LMS adaptive filtering algorithm is applied in the DSP to minimize the mean square error between the filter output signal and the desired signal, thereby enhancing the quality of the output signal. Addressing the limitation of the fixed-step LMS adaptive filtering algorithm, which struggles to balance convergence speed and steady-state accuracy, a genetic algorithm is introduced for global search optimization of variable-step parameters. This enables dynamic updating of variable-step parameters, thereby improving the noise cancellation level of sensor signals.

II. Signal processing method based on improved adaptive filtering algorithm

II. A. Signal Processing System Software Design

The software for the signal processing system uses the integrated development environment Code Composer Studio, with version CCS 9.0 selected. This software offers features such as code editing, code compilation, code debugging, and variable monitoring, greatly facilitating the software design of the signal processing system for experiments. Before use, the actual chip model and simulator model must be set up in the simulator interface. After completing the function code, click the Build option to compile the program. This process not only checks for errors in the program but also converts the code into machine language. Once compilation is complete and it is confirmed that the digital signal processor (DSP) is successfully connected to the computer via the simulator, run the program. This method allows for simulation and debugging of the program using the DSP without the need for program burning. After setting the variable addresses and types in the Graph image display function, the changes in variables can be displayed in real-time during program execution. Variable values in registers can be displayed as graphs or waveforms, facilitating data analysis and observation.

II. A. 1) Signal Processing Flow

Based on the working principle of the MSMA sensor and its external circuitry, the signal processing flow of the MSMA sensor is determined. After the MSMA sensor begins operation, the induced voltage signal output by the sensing coil is sampled by the AD7606 and converted from analog to digital. The DSP reads the signal acquired by the AD7606 and performs mathematical operations on it using a filtering algorithm to obtain the filtered signal. The filtered signal is then processed by the AD5344, converted from digital to analog, and finally produces a pure induced voltage signal that can be observed on an oscilloscope. Figure 1 shows the signal processing flow of the MSMA sensor.

Based on the signal processing flow of the MSMA sensor, the software design of the sensor signal processing system primarily consists of three parts: signal acquisition, DSP filtering, and analog-to-digital conversion.

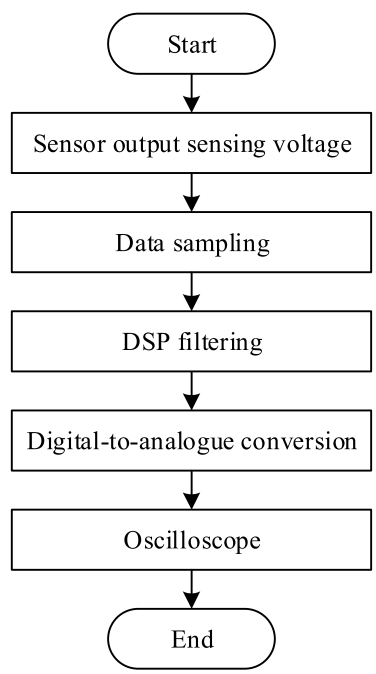


Figure 1: Signal processing flow chart

II. A. 2) Signal Acquisition Design

The AD7606 must first be initialized. When the RESET pin receives a high-level reset signal, the ADC stops the analog-to-digital conversion and performs a reset operation. After the reset is complete, the DSP sets the RESET pin to low, indicating the end of the reset process. When the level of the CONVST pin rises, a BUSY signal with a pulse width of approximately $4.0\mu s$ is generated, indicating the start of data acquisition. The sample-and-hold amplifier converts the sensed voltage signal from analog to digital using binary encoding. When the BUSY signal automatically goes low, it indicates the end of the conversion. Then, control CS and RD to be low levels to begin reading data. Before the read operation, the data lines DB0-DB15 are in a high-impedance state. Only when CS and RD are both low levels will the data lines DB0-DB15 no longer be in a high-impedance state. After data reading is complete, the CONVST signal is pulled low again to prepare for the next conversion.

II. B.Analysis and Application of LMS Adaptive Filtering Algorithm

II. B. 1) Principle of the Least Mean Squares (LMS) Algorithm

The minimum mean square error (MMSE) algorithm simplifies the calculation of gradient vectors by appropriately adjusting the objective function. It is characterized by simplicity, efficiency, low computational complexity, good convergence in stable environments, unbiased convergence to the Wiener solution, ease of implementation, and excellent performance under various operating conditions, making it widely applied in practical designs.

The minimum mean square error algorithm based on the least descending method is the most basic algorithm. It is a recursive algorithm that does not require knowledge of the prior statistical characteristics of the signal but only uses their instantaneous estimated values. Its objective is to minimize the mean square error (MSE) between the expected output value and the actual output value of the filter.

Figure 2 shows a horizontal adaptive filter.

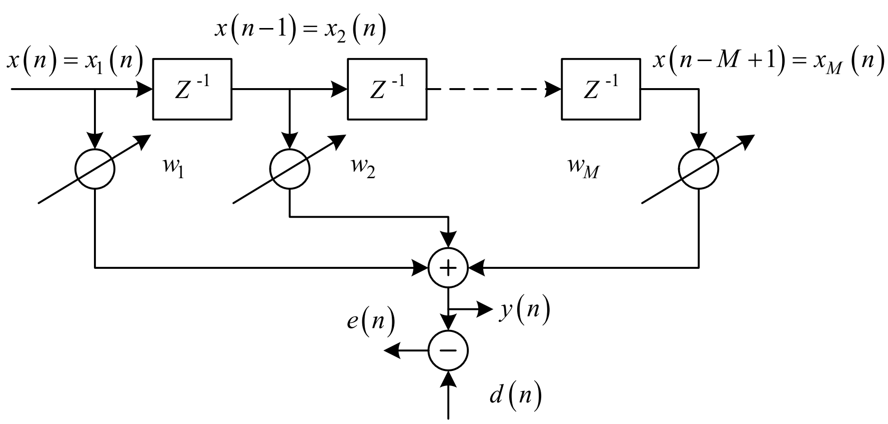


Figure 2: Horizontal adaptive filter

For the filter in Figure 2, the input vector is

$$\begin{aligned} x(n) &= [x_1(n), x_2(n), x_3(n), \ldots, x_M(n)]^T \\ &= [x(n), x(n-1), \ldots, x(n-M+1)]^T \end{aligned} \tag{1}$$

Its weighted vector (i.e., the filter's parameter vector) is

$$w = [w_1, w_2, \ldots, w_M]^T \tag{2}$$

The output of the filter is

$$y(n) = \sum_{i=1}^{M} w_i x(n-i+1) = w^T x(n) = x^T(n) w \tag{3}$$

The error of $y(n)$ relative to the expected signal is

$$e(n) = d(n) - y(n) = d(n) - w^T x(n) \tag{4}$$

According to the minimum mean square error criterion, the optimal filter parameter vector w_{opt} should minimize the performance function—mean square error $f(w) = E\{e^2(n)\}$.

This problem can be viewed as estimating $d(n)$ based on a linear combination of $x(n)$ and its past values $x(n-1), \ldots, x(n-M+1)$, etc. The optimal value of w should minimize the mean square error of the estimate.

Assume that $x(n)$ and $d(n)$ are stationary processes, and let the autocorrelation function of $x(n)$ be $R_{xx} = E\{x(n)x^T(n)\}$, the cross-correlation function of $d(n)$ and $x(n)$ is $R_{xd} = E\{x(n)d(n)\}$, and the mean squared error performance function is defined as $f(w) = E\left\{\left|d(n) - w^T x(n)\right|^2\right\}$ is defined. To minimize the mean square error, the partial derivative formula $\frac{\partial}{\partial w} f(w) = 0$ must be satisfied, because the partial derivative

$\frac{\partial}{\partial w} f(w) = -2R_{xd} + 2R_{xx} w(n)$, the optimal FIR mode filter weight vector w_{opt} under minimum mean square error should satisfy:

$$R_{xx} w_{opt} = R_{xd} \tag{5}$$

When R_{xx} is full rank, the equation has a unique solution.

$$w_{opt} = R_{xx}^{-1} R_{xd} \tag{6}$$

Therefore, the optimal weight vector of the FIR lateral filter under minimum mean square error is $w_{opt} = R_{xx}^{-1} R_{xd}$, which is called the Wiener solution. This is the classic Wiener filter. It can be seen that the solution of this filter is continuously updated as the signal and interference environment change, and it only exhibits optimal behavior in terms of mean square error for stationary processes with corresponding statistical properties. It is not applicable to non-stationary signals. The advantage of this method is its speed, but its drawback is the significant computational complexity required. Especially when the number of weighting coefficients is large, the computational complexity becomes even greater, limiting its practical application. A recursive approach can be used to implement the aforementioned filter. This involves assuming that the recursive process starts from any initial value of the weight vector and continuously adjusts the weight vector values according to an "adaptive algorithm" driven by a certain measure or estimate of the mean square error, ultimately converging to the optimal value, i.e., the Wiener value. This filter can adjust itself to optimal weights without requiring any prior statistical knowledge of the input process, indicating that it possesses a certain degree of tracking capability for changes in input signal characteristics. Regardless of how the input signal characteristics change, it always attempts to adjust its own parameters to minimize the output mean square error. Specifically, for non-stationary input signals, the ability of this adaptive filter to track changes in input characteristics depends on the performance of the adaptive algorithm.

II. B. 2) Application of Adaptive Filters in Noise Cancellation

Adaptive filters have been widely used in noise cancellation. Figure 3 shows the noise cancellation model of an adaptive filter.

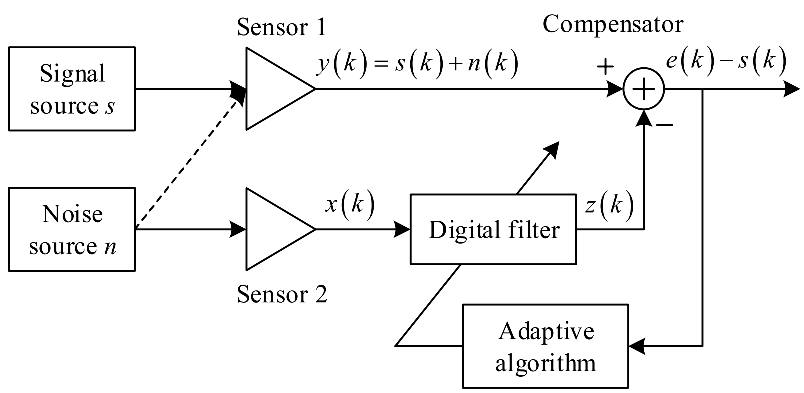


Figure 3: Adaptive filter noise cancellation model

Adaptive filters exhibit excellent filtering performance for linearly correlated noise but are somewhat inadequate for filtering out nonlinearly correlated noise. Below, we conduct a simulation experiment to investigate whether adaptive filters meet the requirements for filtering non-linearly correlated noise. In the noise elimination simulation experiment, when the input signal is a sine wave $s = a * \sin(0.05 * pi * t)$ and the noise signal is a Gaussian noise signal with a mean of 0.0 and an amplitude of 4.0 dB, the input signal and noise signal are non-linearly correlated. The filtering performance of the adaptive filter for nonlinear noise is sufficient to meet the requirements.

II. C.LMS parameter optimization based on genetic algorithms

II. C. 1) Variable Step Size Parameter Optimization of Genetic Algorithms

Genetic algorithms are global optimization algorithms that are widely used in machine learning, signal processing, adaptive control, and other fields. When used in combination with LMS adaptive filtering algorithms, genetic algorithms can improve the convergence performance and stability of adaptive filters.

The fitness function (7) can be obtained based on the factors of the genetic algorithm.

$$\begin{cases} find: x=[\alpha,\beta,\mu(n)], x\in\Delta \\ \min: fitness(x)=(\alpha^{n-1}[u_0+(\mathrm{E}_0)/(\alpha-1)]-u(n+1))\,(\alpha-1)/\beta \end{cases} \tag{7}$$

When designing core genetic operators using genetic algorithms, operators for mutation, crossover, and selection can be used. The general steps are as follows:

1) Operators in the form of crossover are mainly used to provide more opportunities for recombination during gene exchange. Suppose that two individuals are, and perform arithmetic crossover between these two individuals. After the crossover is complete, the two new individuals can be represented as (8):

$$\begin{cases} x_1=(1-\varphi)x_1+\varphi x_2 \\ x_2=(1-\varphi)x_2+\varphi x_1 \end{cases} \tag{8}$$

According to genetic algorithms, when the fitness value obtained from the calculation is smaller, it is closer to the optimal solution in the calculation process, and the possibility of optimal individuals existing in the vicinity is greater. Therefore, we may define the formal parameter (9):

$$\varphi=\frac{fitness(x_1)}{fitness(x_1)+fitness(x_2)} \tag{9}$$

As can be seen, when the form parameters are small, the new individuals are very similar to the original individuals. This allows for searching around individuals with smaller fitness values, thereby increasing the probability of obtaining the optimal individual.

2) When using mutation operators, the primary goal is to prevent the population from getting stuck in local optima during genetic optimization, thereby failing to achieve global optimization. To make mutations more efficient, multiple individuals are randomly selected over a wide range to replace the mutated individuals in the genetic algorithm process. This not only effectively preserves the optimal values of the previous generation but also helps ensure global search in the genetic algorithm through mutation operators.

3) When using genetic operators, the primary goal is to ensure that superior parent generations are inherited while inferior offspring are eliminated. During the search process, a random paired search similar to a football league is employed to inherit individuals with lower fitness into the next generation's new population, with particular attention given to preserving the least fit individuals, ultimately achieving optimal selection.

II. C. 2) Parameter optimization of the cosine function variable step size algorithm

Using a genetic algorithm to optimize the parameters of the variable stride length adaptive algorithm based on the cosine function, the formula can be transformed as follows:

$$\mu(n)=\beta\left(1-\cos\left(\frac{\pi}{\gamma}|e(n)|^{\alpha}\right)\right) \tag{10}$$

After transformation, we obtain:

$$|e(n)|^{\alpha}=\frac{\gamma}{\pi}ar\cos\left(\frac{\beta-\mu(n)}{\beta}\right) \tag{11}$$

Further, we can obtain:

$$|e(n)|^{2}=\left(\frac{\gamma}{\pi}ar\cos\left(\frac{\beta-\mu(n)}{\beta}\right)\right)^{2/\alpha} \tag{12}$$

Using formula (12) as the fitness formula, develop a suitable algorithm:

$$\begin{cases} find: x=[\alpha,\beta,\gamma,\mu(n)], x\in\Delta \\ \min: fitness(x)=\left(\frac{\gamma}{\pi}ar\cos\left(\frac{\beta-\mu(n)}{\beta}\right)\right)^{2/\alpha} \end{cases} \tag{13}$$

Next, design the core operator of the genetic algorithm to perform parameter optimization.

Similarly, to perform parameter optimization for the COS2LMS algorithm, first perform the transformation to obtain:

$$|e(n)|^{2}=\left(\frac{2}{\pi}ar\cos\left(\frac{\beta(\gamma+1)}{\beta+\mu(n)+\gamma}-\gamma\right)\right)^{2/\alpha} \tag{14}$$

The fitness function is (15):

$$\begin{cases} find: x=[\alpha,\beta,\gamma,\mu(n)], x\in\Delta \\ \min: fitness(x)=\left(\dfrac{2}{\pi}ar\cos\left(\dfrac{\beta(\gamma+1)}{\beta+\mu(n)+\gamma}-\gamma\right)\right)^{2/\alpha} \end{cases} \tag{15}$$

II. C. 3) Comparison of algorithms after parameter optimization

Whether there exists an optimal step size iteration method that maximizes the convergence performance of the variable step size KMS algorithm has always been an important research goal for experts and scholars in the field of LMS algorithms. After making some assumptions and approximations in the theory, various approximate optimal variable step size LMS algorithms have emerged based on different optimal rules. Among them, the Shin algorithm is a representative approximate optimal step size algorithm.

The step size factor formula for the Shin algorithm is:

$$\mu_{opt}(n)=\frac{\mu_{\max}\left\|g(n)\right\|^2}{\left\|x(n)\right\|^2\left(c+\left\|g(n)\right\|^2\right)} \tag{16}$$

Among them, $g(n)$ is obtained by taking a smooth approximation of the gradient vector.

$$g(n)=\beta g(n-1)+(1-\beta)\frac{e(n)x(n)}{\left\|x(n)\right\|^2} \tag{17}$$

The step size factor ranges from:

$$0<\mu(n)<\mu_{\max} \tag{18}$$

The weight coefficient update formula for the Shin algorithm is:

$$\omega(n)=\omega(n-1)+\frac{\mu_{opt}(n)x(n)}{\left\|x(n)\right\|^2} \tag{19}$$

A comparative simulation experiment was conducted in the MATLAB environment between the approximate optimal step size algorithm (Shin algorithm) and the parameter-optimized cosine function improved algorithm. The comparison revealed that the COSLMS algorithm had the fastest convergence speed, followed by the COS2LMS algorithm, while the approximate optimal step size Shin algorithm had the slowest convergence speed. However, the steady-state error of COSLMS is the smallest, followed by the steady-state error of the Shin algorithm, with the steady-state error of COS2LMS being the largest. This indicates that parameter optimization can enhance the convergence performance of the improved LMS algorithm. However, it also suggests that parameter optimization is merely an important factor influencing the algorithm's convergence performance, with the decisive factor being the algorithm's inherent structure.

III. Signal processing practices based on improved LMS adaptive filtering

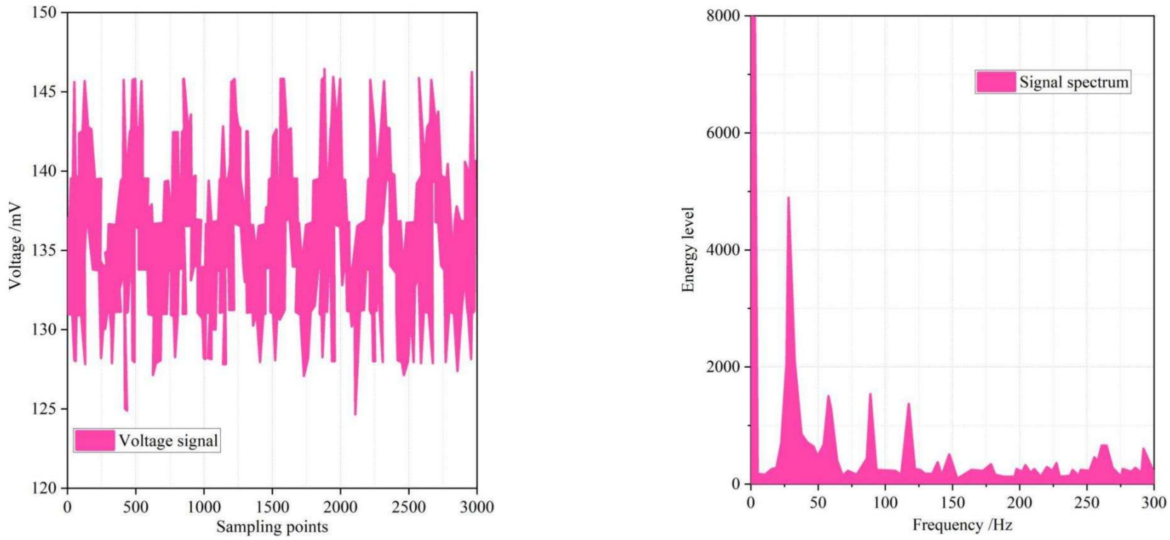
III. A. Preprocessing of sensor signals

III. A. 1) Raw Data and Its Spectrum

The following analysis focuses on the voltage signal data collected by a specific MSMA sensor in an experiment involving noise reduction of simulated inductive voltage signals. Figure 4 shows the raw signal data and its spectrum. The voltage signals collected by the sensor at 3,000 sampling points ranged between 120 mV and 150 mV, with a minimum of 124.65 mV and a maximum of 146.44 mV. The signal frequency ranges from 0 to 300 Hz, with higher signal levels between 0 and 125 Hz and lower signal levels between 125 and 300 Hz, where there may be a significant amount of noise.

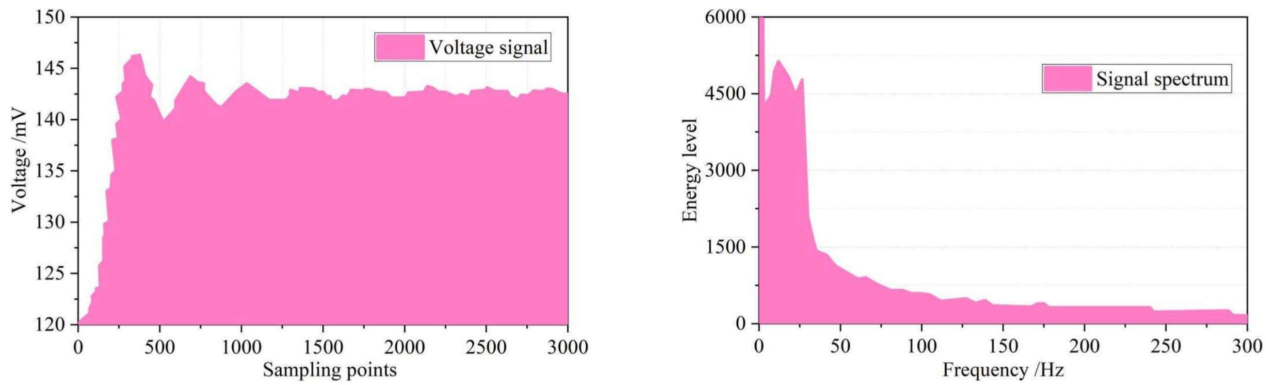
III. A. 2) Sensor signal preprocessing based on traditional filter methods

To validate the signal processing performance of the LMS adaptive filter used in this paper, this section first employs a low-pass filter as a signal preprocessing comparison to determine whether traditional filtering preprocessing methods can achieve the desired signal preprocessing results. Figure 5 shows the signal and spectrum after low-pass filtering. As shown in Figure 5, the waveform after low-pass filtering loses the oscillation characteristics of the original signal in the initial segment from 0 to 300 sampling points, resulting in time delay and phase shift, with significant waveform distortion and severe distortion. Additionally, the spectrum shows that the filtered signal in the 0-50 Hz frequency range contains frequency components not present in the original signal, indicating that the separation and extraction process did not achieve the desired results. Therefore, traditional filtering methods are insufficient for preprocessing sensor signals, and further consideration should be given to the LMS adaptive filtering algorithm with variable step size parameter optimization.



(a) Original signal (b) Frequency /Hz

Figure 4: The collected raw signal data and its spectrum



(a) Filtered signal (b) Signal spectrum

Figure 5: The signal and spectrum after low-pass filtering

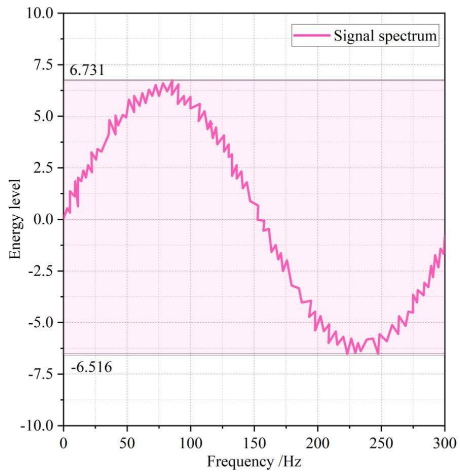
III. A. 3) Signals from different frequency channels after LMS adaptive filter decomposition

Set the signal-to-noise ratio (SNR) of the input signal to SNR=15. Perform filter simulation on the sensor-acquired signals using a DSP. Figure 6 shows the signals from different frequency channels after LMS adaptive filter decomposition. After LMS adaptive filtering decomposition, the energy level of the low-frequency channel signal is between [-6.516, 6.731], and the basic characteristics of the signal are retained to the greatest extent. However, the energy level of the high-frequency channel signal is between [-2.991, 1.925], and the noise characteristics are stronger. Further parameter optimization of the variable step size is required to improve the noise reduction capability of the high-frequency channel signal.

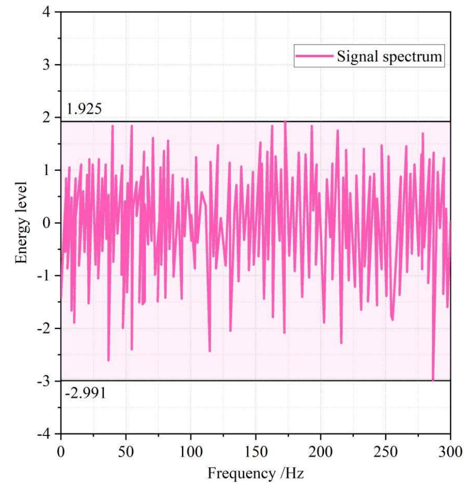
III. B. Algorithm simulation and result analysis under different variable step sizes

III. B. 1) Algorithm processing results when the step size factor is 1/250

Figure 7 shows the signal processing results of the LMS adaptive filter algorithm when the step factor is set to 1/250. When the step factor is set to 1/250, the signal level after processing by the LMS adaptive filter algorithm ranges from -4.597 to 4.452. As can be seen from the signal waveform, the signal still exhibits certain noise characteristics at this point.



(a) Low-frequency scale channel



(b) High-frequency scale channel

Figure 6: The signal decomposed by LMS adaptive filtering

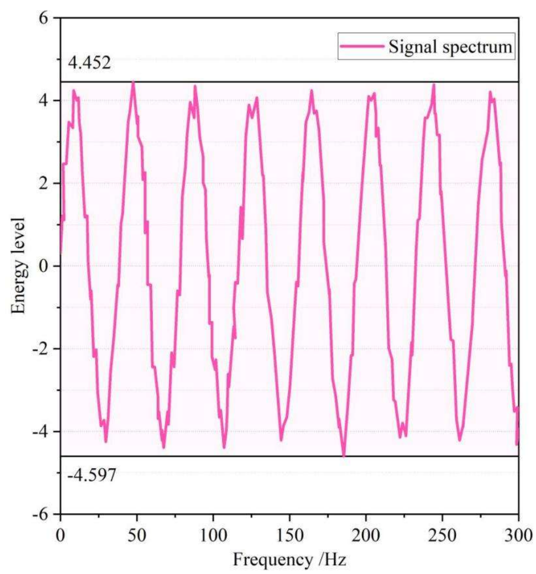


Figure 7: The processing result of the algorithm of 1/250 step factor

III. B. 2) Algorithm processing results when the step size factor is 1/500

Figure 8 shows the signal processing results of the LMS adaptive filtering algorithm when the step size factor is 1/500. When the step size factor is set to 1/500, the signal level range after processing by the LMS adaptive filtering algorithm is [-3.098, 3.217]. At this point, the signal waveform is relatively smooth and does not exhibit noise characteristics. Therefore, a step size factor of 1/500 can effectively reduce noise in the signal. It can also be concluded that the smaller the step size factor, the better the signal processing effect.

III. C. Selection of threshold functions

III. C. 1) Comparison of different threshold functions

Whether filtering can achieve good results for noisy signals depends not only on optimizing the variable step size parameter but also on the selection of the threshold function. Commonly used threshold functions include soft and hard threshold functions. Each of these threshold functions has its own characteristics. For noisy signals, using a hard threshold function sets a threshold based on the magnitude of the signal, where coefficients below the threshold are removed and those above the threshold are retained. This ignores the differences in the retained coefficients, which can easily cause local signal jitter. In contrast, soft thresholding produces smoother denoising results but reduces the clarity of the output. In this section, we apply soft and hard threshold functions to denoise high-frequency signals, with a decomposition layer count of 2. Figure 9 shows the high-frequency voltage signals after denoising using the two threshold functions. The hard function exhibits singular values at 24.22s, 110.72s, 112.64s, and 115.10s; the soft function only exhibits a singular value at 14.44s. Therefore, this paper selects the soft function as the threshold function for signal processing.

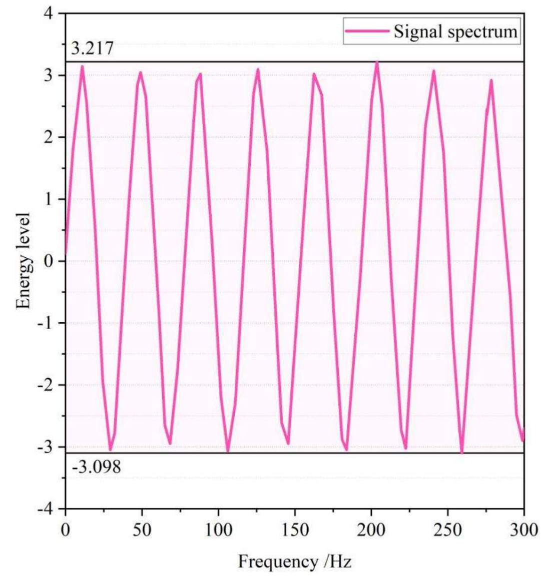


Figure 8: The processing result of the algorithm of 1/500 step factor

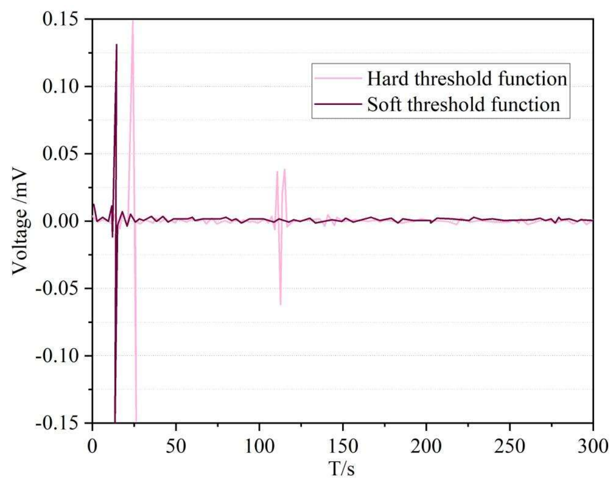


Figure 9: The signals after noise reduction by two threshold functions

III. C. 2) Selection of the number of filter decomposition layers

Since the number of filter decomposition layers was set to only 2 layers in the experiment where the threshold function was selected, this section sets up a comparison experiment to determine the optimal number of filter decomposition layers, testing the noise reduction effects (soft function) corresponding to 2, 3, 4, and 5 layers of filter layers. Figure 10 shows the filtering processing effects for different decomposition layer numbers. When the filtering decomposition layer number is set to 2 or 4 layers, only one singular value appears. Since the signal waveform is smoother and contains less noise when the decomposition layer number is set to 4 layers, it is determined that the signal processing effect is better when the filtering decomposition layer number is set to 4.

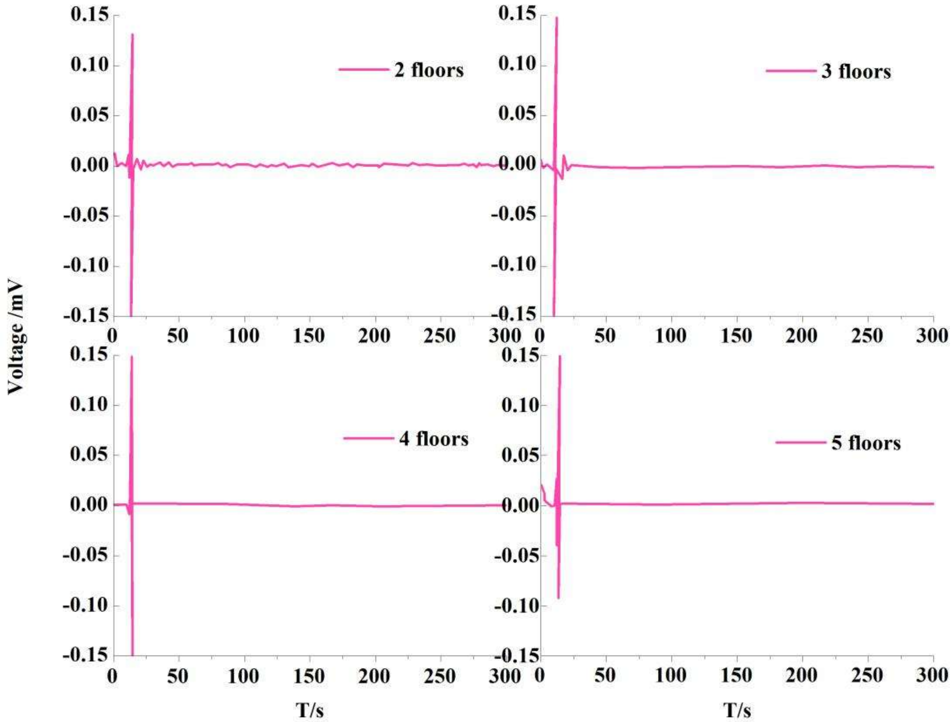


Figure 10: The filtering processing effects of different layers

IV. Conclusion

This paper proposes a sensor signal denoising method based on the LMS adaptive filtering algorithm and genetic algorithm to improve the noise suppression accuracy of the signal. The proposed algorithm achieves better signal processing performance than traditional filtering methods in both low-frequency and high-frequency channels. When the step size factor is set to 1/500, the signal processing performance is better than when it is set to 1/250. When the threshold function is set to a soft function, the signal denoising effect is better, and when the number of filtering decomposition layers is 4, only one singular value appears, resulting in less waveform noise. Future research can validate the robustness of the algorithm in multi-channel sensors and improve its sensor signal denoising capability.

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