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ADAPTIVE PARAMETER OPTIMIZATION STRATEGY FOR DIGITAL SPEECH ENHANCEMENT BASED ON ACOUSTIC NOISE CHARACTERISTICS

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Abstract

Speech enhancement has become one of the most significant research areas in digital signal processing due to the increasing demand for high-quality speech transmission in modern multimedia and communication systems. Environmental noise considerably degrades speech intelligibility, affects automatic speech recognition accuracy, and reduces the overall quality of voice communication. Although adaptive digital filtering techniques have been extensively investigated over the past decades, their effectiveness strongly depends on appropriate parameter selection under dynamically changing acoustic environments.

This paper proposes a conceptual adaptive parameter optimization strategy for digital speech enhancement based on acoustic noise characteristics. Unlike conventional approaches employing fixed adaptation parameters, the proposed framework dynamically adjusts filter coefficients according to estimated environmental conditions. A comprehensive review of adaptive filtering algorithms, including Least Mean Square (LMS), Normalized Least Mean Square (NLMS), Wiener filtering, Recursive Least Squares (RLS), and Kalman filtering, is presented. Their mathematical properties, convergence characteristics, computational complexity, robustness, and practical implementation issues are analyzed. The study demonstrates that adaptive parameter optimization represents a promising direction for future speech enhancement systems capable of achieving improved intelligibility while maintaining computational efficiency.

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The proposed methodology provides the theoretical foundation for developing next-generation adaptive speech enhancement algorithms suitable for multimedia communication, mobile devices, hearing assistance systems, and intelligent audio technologies.

Keywords: Speech Enhancement Adaptive Digital Filtering Noise Reduction Adaptive Parameter Optimizatio Digital Signal Processing Acoustic Noise Speech Processing Audio Technologies.

Introduction

Digital speech communication has become an essential component of modern information technologies. Voice communication is widely used in mobile communications, online conferencing, intelligent assistants, healthcare systems, industrial monitoring, hearing aids, and human–computer interaction. However, the quality of transmitted speech is often degraded by environmental noise originating from traffic, industrial machinery, crowded public places, office environments, and electronic devices. Noise contamination significantly reduces speech intelligibility, affects user experience, and decreases the performance of automatic speech recognition systems. Consequently, speech enhancement has remained one of the most active research fields in digital signal processing for more than four decades.

Numerous digital filtering algorithms have been developed to suppress background noise while preserving useful speech information. Classical approaches include Wiener filtering, adaptive Least Mean Square (LMS) filtering, Normalized Least Mean Square (NLMS), Recursive Least Squares (RLS), Kalman filtering, spectral subtraction, and wavelet-based denoising methods. More recently, deep learning-based speech enhancement techniques have demonstrated remarkable performance improvements. Nevertheless, these methods usually require large annotated datasets, high computational resources, and powerful hardware accelerators.

In contrast, adaptive digital filtering remains attractive because of its low computational complexity, high interpretability, and suitability for real-time applications. However, one fundamental limitation remains unresolved: the performance of adaptive filters strongly depends on parameter selection. Fixed adaptation coefficients often lead to slow convergence, unstable behavior, or insufficient noise suppression when acoustic conditions change dynamically.

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Therefore, adaptive parameter optimization has emerged as an important research direction. Instead of designing completely new filtering algorithms, researchers increasingly focus on improving the adaptation mechanisms of existing filters to increase robustness under non-stationary noise environments.

The objective of this study is to develop a conceptual framework for adaptive parameter optimization based on acoustic noise characteristics. The paper analyzes the limitations of existing adaptive filtering methods, identifies current research challenges, and proposes a methodology for dynamically selecting filtering parameters according to environmental conditions. The scientific contribution of this research lies in establishing a theoretical basis for future development of adaptive speech enhancement algorithms capable of achieving improved performance without significantly increasing computational complexity

2. Literature Review

2.1 Development of Speech Enhancement Technologies

Speech enhancement has been an active research field since the early development of digital signal processing. Initial studies primarily focused on reducing stationary background noise using classical linear filtering techniques. Among these, the Wiener filter became one of the first mathematically optimal solutions because it minimizes the mean square error (MSE) between the desired clean speech signal and the estimated output.Subsequently, adaptive filtering algorithms were introduced to overcome the limitations of fixed filters operating in dynamically changing acoustic environments. The Least Mean Square (LMS) algorithm became one of the most widely adopted adaptive techniques due to its simple implementation and low computational complexity. Later, the Normalized Least Mean Square (NLMS) algorithm improved convergence characteristics by normalizing the adaptation coefficient according to the input signal energy.Recursive Least Squares (RLS) and Kalman filtering further enhanced estimation accuracy and convergence speed. However, their computational complexity significantly increased, making them less suitable for embedded real-time speech processing systems.

During the last decade, deep learning-based speech enhancement methods have attracted considerable attention. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), and Transformer-based architectures have demonstrated remarkable performance in suppressing highly

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non-stationary noise. Nevertheless, these methods require large-scale training datasets, powerful Graphics Processing Units (GPUs), and high computational resources, limiting their practical implementation in low-power devices.
Consequently, adaptive digital filtering remains an important research area because of its computational efficiency, interpretability, and suitability for real-time applications.

2.2 Classical Digital Filtering Methods

Classical digital filters can generally be divided into two major categories:

- Finite Impulse Response (FIR) filters;
- Infinite Impulse Response (IIR) filters.

FIR filters exhibit unconditional stability and linear phase characteristics, making them particularly suitable for speech processing applications. However, they usually require higher filter orders. In contrast, IIR filters achieve similar frequency responses using significantly fewer coefficients. Nevertheless, their nonlinear phase response and potential stability problems often complicate practical implementation.
The transfer function of a general digital filter is expressed as

2. LITERATURE REVIEW

2.1 Development of Speech Enhancement Methods

Speech enhancement has been one of the most important research areas in digital signal processing over the last four decades. The primary objective of speech enhancement is to suppress background noise while preserving the original speech information. High-quality speech enhancement improves communication systems, automatic speech recognition, hearing aids, mobile devices, and multimedia applications. Initially, researchers proposed linear digital filtering methods for stationary noise suppression. Among these approaches, the Wiener filter became one of the most widely used algorithms because it minimizes the mean square estimation error between the desired speech signal and the estimated output.
Later, adaptive filtering algorithms such as Least Mean Square (LMS), Normalized Least Mean Square (NLMS), Recursive Least Squares (RLS), and Kalman filtering were introduced to improve filtering performance in non-stationary acoustic environments. Recent studies have shifted toward intelligent speech enhancement techniques based on deep learning. Although these approaches achieve high speech

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quality, they usually require large datasets, expensive computational hardware, and extensive training procedures. Consequently, adaptive digital filtering remains attractive because of its low computational complexity and real-time implementation capability.

2.2 Digital Speech Signal Model

A speech signal is generally represented as the sum of the clean speech signal and environmental noise.

Eq (1) $y(n) = s(n) + d(n)$

where

- **$y(n)$** – observed noisy speech signal
- **$s(n)$** – clean speech signal
- **$d(n)$** – additive noise

The objective of speech enhancement is to estimate **$s(n)$** from the observed signal **$y(n)$** while minimizing distortion.

The estimation error is defined as **(2) $e(n) = s(n) - \hat{s}(n)$**

where

- **$\hat{s}(n)$** – estimated speech signal

An efficient speech enhancement algorithm attempts to minimize this error throughout the filtering process.

2.3 Noise Characteristics

Environmental noise significantly affects speech quality. Different types of noise exhibit different statistical properties and therefore require different filtering strategies. The most common noise categories include:

- White Gaussian Noise
- Pink Noise
- Brown Noise
- Babble Noise
- Vehicle Noise
- Industrial Noise
- Office Noise
- Wind Noise
- Impulse Noise

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Stationary noise generally maintains nearly constant statistical properties over time. Non-stationary noise changes continuously, making speech enhancement considerably more difficult. Consequently, adaptive filtering algorithms have become the preferred solution for modern speech enhancement systems.

2.4 Frequency Domain Representation

Speech signals are commonly analyzed in the frequency domain using the Discrete Fourier Transform (DFT). The DFT is defined as **(3)** $X(k) = \Sigma\, x(n) \cdot e^{(-j2\pi kn/N)}$
where

- **N** – number of samples
- **k** – frequency index

The inverse transform is **(4)** $x(n) = (1/N)\, \Sigma\, X(k) \cdot e^{(j2\pi kn/N)}$
Frequency-domain analysis enables more efficient separation of speech and noise components. For non-stationary speech signals, the Short-Time Fourier Transform (STFT) is widely employed. **(5)** $STFT(m,k) = \Sigma\, x(n) \cdot w(n-m) \cdot e^{(-j2\pi kn/N)}$
where

- **w(n)** – window function
- **m** – frame index

STFT provides simultaneous time-frequency information, making it suitable for speech enhancement applications.

2.5 Power Spectral Density

The Power Spectral Density (PSD) describes the distribution of signal power over frequency. **(6)** $PSD(f) = |X(f)|^2$ PSD estimation plays an important role in Wiener filtering, spectral subtraction, and adaptive filtering algorithms. Accurate estimation of the noise power spectrum directly influences filtering performance.

2.6 Existing Research Gap

Although numerous adaptive filtering algorithms have been proposed, several scientific challenges remain unresolved.

First, most adaptive filters use fixed learning parameters that cannot efficiently respond to rapidly changing acoustic environments. Second, many studies evaluate filtering algorithms individually instead of investigating adaptive parameter optimization. Third, modern deep learning approaches require significant computational resources, which limits their application in embedded and mobile

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devices. Finally, only a limited number of studies investigate adaptive parameter optimization as an independent research direction for classical digital filtering.
Therefore, there is a need to develop adaptive optimization strategies capable of dynamically adjusting filter parameters according to environmental noise characteristics while maintaining low computational complexity and real-time operation.

3. MATHEMATICAL BACKGROUND

3.1 Mathematical Model of Speech Signal

Speech is a non-stationary random signal whose amplitude and frequency continuously change over time. During transmission, the original speech signal is contaminated by environmental noise, resulting in a noisy observation.
The mathematical model of the received signal is expressed as **(7)** $y(n) = s(n) + d(n)$
where
$y(n)$ – observed noisy speech signal
$s(n)$ – original speech signal
$d(n)$ – additive background noise
The objective of speech enhancement is to estimate the original speech signal $\hat{s}(n)$ from the observed signal while minimizing estimation error.
The estimation error is **(8)** $e(n) = s(n) - \hat{s}(n)$
where
$\hat{s}(n)$ represents the estimated speech signal after filtering.
The Mean Square Error (MSE) criterion is commonly used to evaluate estimation accuracy. **(9)** $MSE = (1/N)\, \Sigma[e(n)]^2$
where
N denotes the total number of speech samples. The adaptive filtering process attempts to minimize the MSE value continuously during operation.

3.2 Statistical Characteristics of Speech Signals

Speech signals possess both deterministic and stochastic properties. Consequently, statistical analysis plays an important role in speech enhancement.
The expected value of a speech signal is **(10)** $E[x] = \Sigma\, x \cdot P(x)$
where
$P(x)$ is the probability distribution of the signal.

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The signal variance is **(11)** $\sigma^2 = E[(x - \mu)^2]$
where
μ is the mean value of the signal.
Standard deviation is **(12)** $\sigma = \sqrt{\sigma^2}$
These statistical parameters describe signal fluctuations and are frequently employed during adaptive parameter estimation.

3.3 Signal Energy

The energy of a discrete speech signal is calculated as **(13)** $E = \Sigma |x(n)|^2$ Average signal power is **(14)** $P = (1/N) \Sigma |x(n)|^2$ These parameters are widely used in adaptive filtering and speech quality evaluation.

3.4 Signal-to-Noise Ratio

One of the most important performance indicators in speech enhancement is the Signal-to-Noise Ratio (SNR).
It is defined as **(15)** $SNR = 10 \log_{10} (Psignal / Pnoise)$
where
Psignal represents speech power, **Pnoise** represents noise power. Using signal samples, **(16)** $SNR = 10 \log_{10}[\Sigma s^2(n) / \Sigma d^2(n)]$
Higher SNR values indicate better speech enhancement performance.

3.5 Noise Modeling

Environmental noise can generally be modeled as a random process.
White Gaussian Noise is represented by**(17)** $d(n) \sim N(0,\sigma^2)$ where σ^2 denotes noise variance.
The probability density function is **(18)** $p(x)=1/(\sqrt{(2\pi\sigma^2)}) \cdot \exp(-(x-\mu)^2/(2\sigma^2))$
Gaussian noise is frequently employed as a benchmark during algorithm evaluation because of its well-defined statistical properties.

3.6 Correlation Analysis

Speech enhancement algorithms often rely on correlation analysis.
The autocorrelation function is **(19)** $Rxx(k)=\Sigma\, x(n)x(n-k)$ Cross-correlation between noisy speech and the desired signal is **(20)** $Rxy(k)=\Sigma\, x(n)y(n-k)$ Correlation analysis provides valuable information for estimating adaptive filter coefficients.

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3.7 Frequency Response

The transfer function of a digital filter is **(21) $H(z)=Y(z)/X(z)$** For FIR filters, **(22) $H(z)=b_0+b_1z^{-1}+b_2z^{-2}+...+bMz^{-M}$** For IIR filters, **(23) $H(z)= (b_0+b_1z^{-1}+...+bMz^{-M})/(1+a_1z^{-1}+...+aNz^{-N})$**
The frequency response is obtained by substituting **$z = e^{j}\omega$** givingn**(24) $H(e^{j}\omega)=H(z)|z=e^{j}\omega$** Frequency response analysis enables evaluation of attenuation characteristics across different frequency bands.

3.8 Discussion of the Mathematical Model

The mathematical formulations presented in this section provide the theoretical basis for adaptive speech enhancement. The signal model, statistical analysis, spectral representation, and frequency-domain characteristics establish the foundation required for the development and optimization of adaptive digital filtering algorithms. These mathematical relationships will be utilized in the following section to derive adaptive filtering methods and to formulate the proposed parameter optimization strategy.

4. ADAPTIVE FILTERING ALGORITHMS

4.1 Least Mean Square (LMS) Algorithm

The Least Mean Square (LMS) algorithm is one of the most widely used adaptive filtering techniques because of its simple mathematical structure, low computational complexity, and suitability for real-time speech enhancement systems. The algorithm iteratively updates filter coefficients according to the instantaneous estimation error between the desired signal and the filter output. The output signal of the adaptive filter is calculated as **(25) $y(n) = w^T(n)x(n)$**
where
- **$w(n)$** – adaptive filter coefficient vector;
- **$x(n)$** – input signal vector.

The estimation error is **(26) $e(n) = d(n) - y(n)$**
where
- **$d(n)$** – desired speech signal.

The coefficient update equation is **(27) $w(n + 1) = w(n) + \mu e(n)x(n)$**
where
- **μ** – adaptation step size.

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The convergence condition is **(28)** $0 < \mu < 2 / \lambda_{max}$ where λ_{max} is the largest eigenvalue of the input signal correlation matrix.

Advantages

- Simple implementation.
- Low computational complexity.
- Suitable for real-time applications.
- Low memory requirements.

Limitations

- Slow convergence.
- Sensitive to the choice of step size.
- Performance decreases in rapidly changing noise environments.

4.2 Normalized Least Mean Square (NLMS) Algorithm

The Normalized Least Mean Square (NLMS) algorithm improves the convergence characteristics of LMS by normalizing the adaptation step according to the input signal power. This prevents instability when the input amplitude varies significantly. The adaptive step size is **(29)**$\mu(n) = \mu / (\delta + ||x(n)||^2)$

where

- δ – small positive constant;
- $||x(n)||^2$ – input signal energy.

The coefficient update equation becomes **(30)** $w(n + 1) = w(n) + \mu(n)e(n)x(n)$

Advantages

- Faster convergence.
- Better numerical stability.
- Less sensitive to signal amplitude changes.
- Suitable for non-stationary environments.

Limitations

- Slightly higher computational complexity than LMS.
- Performance still depends on parameter selection.

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4.3 Wiener Filter

The Wiener filter is an optimal linear estimation method that minimizes the Mean Square Error between the desired speech signal and the estimated output.
The optimal filter coefficients satisfy the Wiener-Hopf equation**31)**
Rw = where
- **R** – autocorrelation matrix;
- **w** – filter coefficient vector;
- **p** – cross-correlation vector.

The optimal solution is **(32)** $\mathbf{w} = \mathbf{R}^{-1}\mathbf{p}$ The frequency-domain Wiener filter is expressed as **(33)** $H(f) = Ps(f) / [Ps(f) + Pn(f)]$
where
- **Ps(f)** – speech power spectrum;
- **Pn(f)** – noise power spectrum.

Advantages

- Excellent performance for stationary noise.
- Minimum mean square error solution.
- Stable mathematical formulation.

Limitations

- Requires accurate estimation of noise statistics.
- Performance decreases under rapidly changing noise conditions.

4.4 Recursive Least Squares (RLS) Algorithm

The Recursive Least Squares algorithm minimizes the exponentially weighted least-squares error. Compared with LMS, RLS converges much faster but requires significantly greater computational resources. The objective function is **(34)** $J(n) = \Sigma\ \lambda^{(n-i)} e^2(i)$
where
- λ – forgetting factor ($0 < \lambda \leq 1$).

The gain vector is **(35)** $k(n) = P(n-1)x(n) / [\lambda + x^T(n)P(n-1)x(n)]$
The coefficient update equation is
(36) $w(n) = w(n-1) + k(n)e(n)$

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Advantages
- Very fast convergence.
- High estimation accuracy.
- Effective under rapidly changing conditions.

Limitations
- High computational complexity.
- Large memory consumption.
- Less suitable for low-power embedded devices.

4.5 Kalman Filter

The Kalman filter is a recursive estimation algorithm widely used for dynamic signal tracking and speech enhancement. It estimates the hidden clean speech signal from noisy observations using a state-space model.

The state equation is **(37)** $\mathbf{x(k) = Ax(k-1) + Bu(k) + w(k)}$ The observation equation is **(38)** $\mathbf{z(k) = Hx(k) + v(k)}$

where
- **A** – state transition matrix;
- **H** – observation matrix;
- **w(k)** – process noise;
- **v(k)** – measurement noise.

The Kalman gain is **(39)** $\mathbf{K(k) = P(k)H^T / [HP(k)H^T + R]}$

The state estimate is updated as **(40)** $\mathbf{\hat{x}(k) = \hat{x}(k-1) + K(k)[z(k) - H\hat{x}(k-1)]}$

Advantages
- High estimation accuracy.
- Excellent tracking capability.
- Effective for non-stationary signals.

Limitations
- High computational complexity.
- Difficult parameter tuning.
- Requires accurate system modeling.

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4.6 Comparative Analysis of Adaptive Algorithms

Table 1 presents a comparison of the adaptive filtering algorithms discussed in this study.

Algorithm	Convergence Speed	Computational Complexity	Noise Reduction	Real-Time Suitability
LMS	Moderate	Low	Good	Excellent
NLMS	Fast	Low	Very Good	Excellent
Wiener	Fast	Medium	Excellent (stationary noise)	Good
RLS	Very Fast	High	Excellent	Moderate
Kalman	Very Fast	Very High	Excellent	Limited

The comparison indicates that no single adaptive filtering algorithm performs optimally under all acoustic conditions. LMS and NLMS are suitable for real-time applications due to their computational efficiency, whereas Wiener, RLS, and Kalman filters provide higher estimation accuracy at the cost of increased computational complexity. This observation motivates the development of an adaptive parameter optimization strategy capable of selecting the most appropriate filtering behavior according to changing noise characteristics.

5. PROPOSED ADAPTIVE PARAMETER OPTIMIZATION STRATEGY

5.1 Motivation of the Proposed Method

Despite significant progress in digital speech enhancement, existing adaptive filtering algorithms still face several limitations when operating under dynamically changing acoustic environments. Most conventional adaptive filters employ fixed adaptation parameters that remain unchanged throughout the filtering process. As a result, their performance deteriorates when the background noise characteristics vary over time.
For example, a step size that provides fast convergence under stationary Gaussian noise may become unstable in the presence of impulsive or highly non-stationary noise. Conversely, selecting a very small adaptation coefficient improves stability but significantly slows down convergence and reduces noise suppression performance.
These limitations indicate that the effectiveness of adaptive filtering depends not only on the filtering algorithm itself but also on the proper selection of its internal parameters.

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Therefore, instead of proposing an entirely new adaptive filter, this research focuses on developing an **adaptive parameter optimization strategy** capable of dynamically adjusting filtering parameters according to the estimated acoustic environment.

5.2 General Architecture of the Proposed Method

The proposed framework consists of six sequential processing stages.

Stage 1. Speech Acquisition

The noisy speech signal is acquired from microphones or communication devices.

Stage 2. Noise Analysis

Statistical characteristics of the acoustic environment are estimated, including:

- Signal-to-Noise Ratio (SNR)
- Signal Energy
- Noise Variance
- Power Spectral Density (PSD)

Stage 3. Noise Classification

The analyzed acoustic environment is classified into one of the predefined categories:

- White Noise
- Babble Noise
- Industrial Noise
- Vehicle Noise
- Wind Noise
- Impulse Noise

Stage 4. Adaptive Parameter Optimization

Instead of using constant filter parameters, the algorithm automatically selects

- learning rate μ
- filter order M
- forgetting factor λ

according to the detected acoustic conditions.

Stage 5. Adaptive Filtering

The optimized parameters are applied to the selected adaptive filtering algorithm.

Stage 6. Enhanced Speech Output

The enhanced speech signal is generated and transmitted to the output device.

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5.3 Mathematical Description

The adaptive learning coefficient is no longer constant. Instead, **(41) $\mu = f(SNR, \sigma^2, PSD)$**

where

- **SNR** — Signal-to-Noise Ratio
- **σ^2** — Noise Variance
- **PSD** — Power Spectral Density

This means that the learning coefficient automatically changes according to the acoustic environment.

Similarly, the filter order becomes **(42) $M = g(NT, FC)$**

where

- **NT** — Noise Type
- **FC** — Frequency Characteristics

This enables the adaptive filter to employ different filter structures for different categories of background noise.

5.4 Adaptive Optimization Criterion

The proposed optimization objective minimizes both speech distortion and residual noise simultaneously. The optimization criterion is **(43) $J = \alpha \cdot MSE + \beta \cdot RN$**

where

- **MSE** — Mean Square Error
- **RN** — Residual Noise
- **α** and **β** — weighting coefficients

The optimization problem becomes **(44) min J** subject to **$0 < \mu < 1$** and **$M_{min} \leq M \leq M_{max}$** This formulation ensures stable adaptive filtering while maintaining computational efficiency.

5.5 Expected Advantages

Compared with conventional adaptive filtering methods, the proposed optimization strategy is expected to provide several advantages.

Improved convergence

The adaptive learning coefficient accelerates convergence under rapidly changing acoustic conditions.

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Higher speech quality
Dynamic parameter adjustment reduces residual background noise while preserving speech components.
Better robustness
The algorithm becomes less sensitive to sudden environmental changes.
Lower computational cost
Unlike deep learning approaches, the proposed strategy can be implemented without expensive GPU hardware.
Real-time capability
The computational complexity remains suitable for embedded audio systems, hearing aids, mobile devices, and multimedia communication platforms.

5.6 Scientific Novelty

The scientific novelty of this study can be summarized as follows:
- A conceptual framework for adaptive parameter optimization in digital speech enhancement is proposed.
- The adaptive filter parameters are dynamically adjusted according to acoustic noise characteristics instead of remaining fixed.
- Multiple statistical noise indicators are jointly utilized for parameter optimization.
- The proposed methodology improves the adaptability of classical digital filtering algorithms without significantly increasing computational complexity.
- The framework establishes a theoretical basis for future development of intelligent real-time speech enhancement systems.

6. EXPERIMENTAL DESIGN

6.1 Research Methodology

To evaluate the effectiveness of the proposed adaptive parameter optimization strategy, a comprehensive experimental methodology is developed. The experimental framework is designed to compare the performance of conventional adaptive filtering algorithms with the proposed optimization approach under different acoustic noise conditions.
The research methodology consists of the following stages:
1. Acquisition of clean speech signals.
2. Generation of noisy speech under different acoustic environments.

3. Statistical analysis of the noise characteristics.
4. Dynamic optimization of adaptive filter parameters.
5. Speech enhancement using optimized adaptive filtering.
6. Performance evaluation using objective quality metrics.
7. Comparative analysis of filtering algorithms.

This methodology enables a systematic evaluation of the proposed framework under identical experimental conditions.

6.2 Experimental Environment

The proposed methodology can be implemented using commonly available scientific software platforms.

Software

- MATLAB R2024a (or newer)
- Python 3.12
- NumPy
- SciPy
- Librosa
- MATLAB Signal Processing Toolbox

Hardware

- Intel Core i5/i7 Processor
- 16 GB RAM
- Windows 11 Operating System

Since the proposed optimization strategy is based on adaptive digital filtering rather than deep neural networks, no high-performance GPU is required. This significantly reduces computational cost and facilitates real-time implementation.

6.3 Speech Database

The experimental evaluation employs publicly available speech datasets widely used in speech enhancement research. The speech corpus contains recordings of both male and female speakers sampled at 16 kHz. To evaluate algorithm robustness, different environmental noises are artificially added to clean speech recordings.

The investigated acoustic environments include:

- White Gaussian Noise
- Babble Noise

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- Car Noise
- Industrial Noise
- Street Noise
- Office Noise
- Wind Noise

Different Signal-to-Noise Ratio (SNR) levels are considered:

- −5 dB
- 0 dB
- 5 dB
- 10 dB
- 15 dB
- 20 dB

These conditions represent realistic communication environments encountered in practical speech transmission systems.

6.4 Performance Evaluation Metrics

To objectively evaluate speech enhancement performance, several quantitative metrics are employed.

Mean Square Error (MSE)

The Mean Square Error measures the average squared difference between the original and enhanced speech signals. **(45)** $\mathbf{MSE = (1/N)\, \Sigma\, (s(n) - \hat{s}(n))^2}$

where

- $\mathbf{s(n)}$ – original speech signal
- $\mathbf{\hat{s}(n)}$ – enhanced speech signal

Lower MSE values indicate better filtering performance.

Root Mean Square Error (RMSE)

RMSE is calculated as

Equation (46)

$\mathbf{RMSE = \sqrt{MSE}}$

Smaller RMSE values correspond to higher speech reconstruction accuracy.

Signal-to-Noise Ratio Improvement

The improvement obtained after filtering is computed by **(47)** $\mathbf{\Delta SNR = SNR_{output} - SNR_{input}}$ Positive values indicate successful noise suppression.

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Speech Quality Evaluation

Speech quality is evaluated using the following objective measures:

- PESQ (Perceptual Evaluation of Speech Quality)
- STOI (Short-Time Objective Intelligibility)
- SDR (Signal-to-Distortion Ratio)

These measures provide complementary information about speech quality and intelligibility.

6.5 Comparative Experimental Procedure

The experimental procedure consists of several consecutive steps.

First, clean speech recordings are selected from the speech database.

Second, different environmental noise types are added at predefined SNR levels.

Third, each noisy speech signal is processed using:

- LMS
- NLMS
- Wiener Filter
- RLS
- Kalman Filter

Finally, the proposed adaptive parameter optimization strategy is applied.

The obtained results are compared using identical evaluation criteria to ensure fair performance assessment.

6.6 Expected Experimental Results

Although the experimental implementation represents future work, the proposed methodology is expected to provide the following improvements:

- Faster convergence of adaptive filters.
- Improved speech quality under non-stationary noise.
- Higher SNR improvement.
- Lower MSE and RMSE values.
- Better robustness against changing acoustic conditions.
- Reduced computational complexity compared with deep learning approaches.

These expected outcomes will be validated through experimental implementation in the next stage of the doctoral research.

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7. RESULTS AND DISCUSSION

7.1 Comparative Performance Analysis

The comparative evaluation of adaptive filtering algorithms demonstrates that each method exhibits different strengths depending on the acoustic environment.The LMS algorithm provides low computational complexity and stable real-time performance. However, its convergence speed decreases when processing highly non-stationary noise.

The NLMS algorithm improves convergence by normalizing the adaptation step size, resulting in better stability across varying input signal amplitudes.

The Wiener filter achieves excellent performance in stationary noise environments but requires accurate estimation of noise statistics, limiting its effectiveness under rapidly changing conditions.

The RLS algorithm offers significantly faster convergence than LMS and NLMS, although its computational complexity is considerably higher.

Kalman filtering provides highly accurate signal estimation for dynamic systems but requires precise mathematical modeling and increased computational resources.

The proposed adaptive parameter optimization framework addresses these limitations by dynamically adjusting filter parameters according to the estimated acoustic environment, thereby improving robustness without fundamentally altering the underlying filtering algorithms.

7.2 Comparative Performance Evaluation

To objectively compare the investigated adaptive filtering algorithms, several performance indicators are considered, including convergence speed, computational complexity, noise suppression capability, speech quality preservation, and real-time implementation efficiency.

The comparison reveals that no individual filtering algorithm performs optimally under every acoustic condition. Each method exhibits unique strengths and limitations depending on environmental noise characteristics.

LMS filtering provides satisfactory performance for stationary acoustic environments while maintaining very low computational requirements. Nevertheless, its convergence rate decreases significantly under rapidly changing noise conditions.

NLMS improves convergence by introducing adaptive normalization of the learning coefficient. Consequently, it provides more stable behavior under varying signal amplitudes.
The Wiener filter demonstrates excellent performance when accurate statistical information about background noise is available. However, practical estimation of noise statistics remains a challenging task in real communication systems.
The RLS algorithm achieves significantly faster convergence than LMS and NLMS. Despite its high estimation accuracy, its computational complexity limits its implementation in portable embedded devices.
Kalman filtering exhibits the highest estimation accuracy among the investigated methods. However, its practical application requires accurate mathematical system modeling and considerable computational resources.
The proposed adaptive parameter optimization strategy combines the advantages of existing adaptive filtering algorithms without substantially increasing computational complexity. Instead of modifying the internal mathematical structure of adaptive filters, the proposed methodology dynamically adjusts their operating parameters according to current acoustic conditions.

7.3 Discussion

The obtained theoretical analysis indicates that parameter selection has a direct influence on speech enhancement performance. Fixed adaptation parameters cannot provide optimal performance under all environmental conditions because acoustic noise continuously changes over time.
The proposed adaptive optimization framework attempts to overcome this limitation by introducing dynamic parameter adjustment based on acoustic noise characteristics. Unlike deep learning approaches requiring extensive computational resources and large training datasets, the proposed methodology preserves the mathematical simplicity of classical adaptive filtering while improving its adaptability.
Another important advantage of the proposed framework is its compatibility with existing adaptive filtering algorithms. The optimization strategy can be integrated into LMS, NLMS, RLS, Wiener, or Kalman filtering without requiring complete redesign of their mathematical structures.

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Furthermore, the proposed methodology is suitable for implementation in real-time communication systems, hearing assistance devices, mobile applications, multimedia platforms, and embedded audio processing systems.

The theoretical analysis also suggests that adaptive parameter optimization may reduce speech distortion while simultaneously increasing background noise suppression. These assumptions require experimental validation, which constitutes the next stage of the doctoral research.

7.4 Research Significance

The significance of this research extends beyond conventional speech enhancement techniques.

From a theoretical perspective, the study introduces a generalized adaptive parameter optimization framework applicable to multiple adaptive filtering algorithms.

From a practical perspective, the proposed methodology may improve speech quality in numerous applications, including:

- Mobile communication systems
- Online conferencing platforms
- Intelligent voice assistants
- Hearing aid technologies
- Industrial communication systems
- Automotive voice control
- Human–computer interaction
- Multimedia audio processing

The flexibility of the proposed framework enables adaptation to different acoustic environments without substantially increasing computational requirements.

8. FUTURE RESEARCH DIRECTIONS

The proposed adaptive parameter optimization strategy establishes a theoretical foundation for several future research directions.

The first direction involves the development of an automatic acoustic environment recognition module capable of classifying environmental noise in real time.

The second direction focuses on intelligent optimization of adaptive filter parameters using statistical signal characteristics, including Signal-to-Noise Ratio (SNR), Power Spectral Density (PSD), and noise variance.

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Another promising direction is the integration of lightweight machine learning techniques to support parameter selection without replacing classical adaptive filtering algorithms. Such hybrid systems could improve adaptability while preserving computational efficiency.

Future investigations will also evaluate the proposed methodology using MATLAB and Python simulation environments under various real-world acoustic conditions. Experimental validation will include objective quality metrics such as PESQ, STOI, SDR, SI-SDR, and SNR Improvement.

Finally, the proposed optimization framework may be extended to embedded hardware platforms, including Digital Signal Processors (DSPs), Field Programmable Gate Arrays (FPGAs), and low-power Internet of Things (IoT) audio devices.

9. CONCLUSION

Speech enhancement remains one of the most important research areas in modern digital signal processing due to the increasing demand for reliable voice communication under adverse acoustic conditions. Background noise significantly degrades speech quality, reduces intelligibility, and negatively affects the performance of speech recognition systems and multimedia communication platforms.

This study presented a comprehensive analysis of existing adaptive digital filtering techniques used for speech enhancement in noisy environments. Classical algorithms, including Least Mean Square (LMS), Normalized Least Mean Square (NLMS), Wiener filtering, Recursive Least Squares (RLS), and Kalman filtering, were mathematically analyzed with respect to their convergence behavior, computational complexity, estimation accuracy, robustness, and suitability for real-time implementation.

The literature review demonstrated that although considerable progress has been achieved in adaptive speech enhancement, no single filtering algorithm provides optimal performance under all acoustic conditions. Fixed adaptation parameters remain one of the major limitations of existing adaptive filtering techniques, particularly when processing highly dynamic and non-stationary environmental noise.

To address this limitation, this paper proposed a conceptual adaptive parameter optimization strategy based on acoustic noise characteristics. Unlike conventional approaches that employ constant adaptation parameters, the proposed framework

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dynamically adjusts filter coefficients according to the estimated statistical properties of the acoustic environment. The methodology utilizes multiple signal characteristics, including Signal-to-Noise Ratio (SNR), noise variance, Power Spectral Density (PSD), and acoustic noise classification, to improve adaptive filtering performance.
The proposed framework is expected to provide several advantages, including faster convergence, improved speech quality, enhanced robustness against environmental changes, and reduced computational requirements compared with computationally intensive deep learning approaches. Furthermore, the proposed methodology preserves the mathematical simplicity of classical adaptive filtering algorithms while improving their adaptability to dynamically changing acoustic environments.
The presented research establishes a theoretical foundation for the future development of intelligent adaptive speech enhancement systems. Future work will focus on the practical implementation of the proposed optimization strategy using MATLAB and Python environments, followed by experimental validation under real acoustic conditions. The obtained results will support the development of efficient real-time speech enhancement systems applicable to multimedia communication, hearing assistance devices, mobile technologies, and embedded audio processing platforms

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author Contributions

All authors contributed substantially to the conceptualization, methodology development, literature review, analysis, and preparation of this manuscript.

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The datasets and materials used in this conceptual study are based on publicly available scientific resources. Experimental implementation and validation will be conducted during the subsequent stages of the doctoral research.

Table 1 Comparison of Adaptive Filtering Algorithms

Algorithm	Complexity	Convergence	Noise Reduction	Real-Time
LMS	Low	Medium	Good	Excellent
NLMS	Low	Fast	Very Good	Excellent
Wiener	Medium	Fast	Excellent	Good
RLS	High	Very Fast	Excellent	Moderate
Kalman	Very High	Very Fast	Excellent	Moderate

Table 2 Noise Types Used in Experimental Evaluation

Noise Type	Characteristics	Difficulty
White	Stationary	Low
Babble	Human voices	High
Car	Non-stationary	Medium
Office	Mixed noise	Medium
Wind	Random	High
Industrial	Mechanical	Very High

Table 3 Evaluation Metrics

Metric	Description
SNR	Signal-to-Noise Ratio
MSE	Mean Square Error
RMSE	Root Mean Square Error
PESQ	Speech Quality
STOI	Speech Intelligibility
SDR	Signal-to-Distortion Ratio

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10. Practical Applications

The proposed adaptive parameter optimization strategy can be applied in numerous speech processing systems requiring reliable operation under noisy environments. Potential application areas include mobile communication systems, online conferencing platforms, hearing assistance devices, smart home technologies, automotive voice control systems, multimedia communication, industrial monitoring systems, and intelligent human–computer interaction. Because the proposed framework is based on adaptive digital filtering rather than computationally intensive deep neural networks, it is suitable for real-time implementation on embedded hardware platforms with limited processing resources.

Furthermore, the proposed methodology may serve as a preprocessing stage for automatic speech recognition systems, speaker identification systems, and voice-controlled industrial equipment, improving recognition accuracy by suppressing environmental noise before further signal analysis.

11. Limitations of the Present Study

The present study mainly establishes a theoretical framework for adaptive parameter optimization. Experimental implementation using MATLAB or Python and validation on benchmark speech databases constitute the next stage of the research. In addition, the optimization strategy has not yet been evaluated under all possible real-world acoustic environments. Future work will investigate parameter adaptation under highly dynamic noise conditions and compare the proposed framework with recent lightweight neural speech enhancement techniques.

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