SPEECH SIGNAL ENHANCEMENT IN NOISY ENVIRONMENTS USING HYBRID ADAPTIVE FILTERING AND TRANSFORMER-BASED ARTIFICIAL INTELLIGENCE METHODS

Madina Beknazar qizi Isvandiyarova
Doctoral Student (PhD) Tashkent University of Information Technologies named after Muhammad al-Khwarizmi Department of Multimedia Technologies
Scientific Supervisor: Professor at the Multimedia Department of TUTU
Saida Safibullayevna Beknazarova

Abstract: The rapid development of modern communication technologies has significantly increased the demand for high-quality speech transmission and processing systems. Speech signals are widely used in mobile communication networks, voice assistants, automatic speech recognition systems, teleconferencing platforms, hearing aids, remote education environments, and intelligent human-computer interaction systems. However, in practical scenarios, speech signals are inevitably contaminated by various stationary and non-stationary noise sources, leading to a degradation in speech intelligibility, perceptual quality, and recognition performance.

Traditional speech enhancement approaches, including Wiener filtering, Kalman filtering, spectral subtraction, and adaptive filtering, have demonstrated acceptable performance under stationary noise conditions. Nevertheless, their effectiveness decreases considerably in highly dynamic acoustic environments characterized by non-stationary noise. Recent advances in artificial intelligence, particularly deep learning and Transformer-based architectures, have opened new opportunities for addressing these challenges by modeling complex nonlinear relationships inherent in speech signals.

This paper proposes a hybrid speech enhancement framework that integrates Wiener filtering, Least Mean Squares (LMS) adaptive filtering, and Transformer-based artificial intelligence methods to improve speech quality in noisy environments. The proposed methodology combines the advantages of classical digital signal processing techniques with the powerful representation learning capabilities of modern deep neural networks. Mathematical models of noisy speech signals are developed, and theoretical analyses of adaptive filtering mechanisms are presented. Furthermore, the Transformer architecture is utilized to capture long-range temporal dependencies and contextual information within speech signals.

The proposed hybrid framework aims to reduce background noise while preserving speech intelligibility and minimizing speech distortion. Performance evaluation is conducted using Signal-to-Noise Ratio (SNR), Mean Squared Error

(MSE), and Perceptual Evaluation of Speech Quality (PESQ) metrics. Theoretical analysis indicates that the integration of adaptive filtering and Transformer-based learning can significantly improve speech enhancement performance compared with conventional methods.

Keywords: Speech Enhancement, Adaptive Filtering, LMS Algorithm, Wiener Filter, Transformer Networks, Artificial Intelligence, Deep Learning, Noise Reduction, Speech Processing, Digital Signal Processing.

УЛУЧШЕНИЕ РЕЧЕВОГО СИГНАЛА В УСЛОВИЯХ ШУМА С ИСПОЛЬЗОВАНИЕМ ГИБРИДНОЙ АДАПТИВНОЙ ФИЛЬТРАЦИИ И МЕТОДОВ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА НА ОСНОВЕ ТРАНСФОРМЕРОВ

Мадина Бекназар Кизи Исвандиярова
Аспирант (PhD) Ташкентского университета информационных технологий имени Мухаммада аль-Хорезми, кафедра мультимедийных технологий
Научный руководитель: Профессор кафедры мультимедиа TUTU.
Саида Сафибуллаевна Бекназарова

Аннотация: Быстрое развитие современных коммуникационных технологий значительно увеличило спрос на высококачественные системы передачи и обработки речи. Речевые сигналы широко используются в сетях мобильной связи, голосовых помощниках, системах автоматического распознавания речи, платформах телеконференций, слуховых аппаратах, системах дистанционного обучения и интеллектуальных системах взаимодействия человека с компьютером. Однако в практических сценариях речевые сигналы неизбежно загрязняются различными стационарными и нестационарными источниками шума, что приводит к ухудшению разборчивости речи, качества восприятия и эффективности распознавания.

Традиционные методы улучшения речи, включая фильтрацию Винера, фильтрацию Калмана, спектральное вычитание и адаптивную фильтрацию, продемонстрировали приемлемую эффективность в условиях стационарного шума. Тем не менее, их эффективность значительно снижается в высокодинамичных акустических средах, характеризующихся нестационарным шумом. Последние достижения в области искусственного интеллекта, в частности глубокое обучение и архитектуры на основе трансформеров, открыли новые возможности для решения этих проблем путем моделирования сложных нелинейных взаимосвязей, присущих речевым сигналам.

В данной статье предлагается гибридная структура улучшения качества речи, которая объединяет фильтр Винера, адаптивную фильтрацию методом наименьших квадратов (LMS) и методы искусственного интеллекта на основе трансформеров для повышения качества речи в условиях шума. Предложенная методология сочетает в себе преимущества классических методов цифровой обработки сигналов с мощными возможностями обучения представлений современных глубоких нейронных сетей. Разработаны математические модели зашумленных речевых сигналов и представлен теоретический анализ механизмов адаптивной фильтрации. Кроме того, архитектура трансформеров используется для захвата долговременных временных зависимостей и контекстной информации в речевых сигналах.

Предложенная гибридная структура направлена на снижение фонового шума при сохранении разборчивости речи и минимизации искажений. Оценка производительности проводится с использованием метрик отношения сигнал-шум (SNR), среднеквадратичной ошибки (MSE) и перцептивной оценки качества речи (PESQ). Теоретический анализ показывает, что интеграция адаптивной фильтрации и обучения на основе трансформеров может значительно улучшить качество улучшения речи по сравнению с традиционными методами.

Ключевые слова: улучшение качества речи, адаптивная фильтрация, алгоритм LMS, фильтр Винера, трансформаторные сети, искусственный интеллект, глубокое обучение, шумоподавление, обработка речи, цифровая обработка сигналов.

Introduction

Speech communication represents one of the most natural and effective forms of information exchange between humans. With the emergence of next-generation communication systems and intelligent technologies, speech signals have become a critical component of modern digital infrastructures. Applications such as voice-over-IP systems, virtual assistants, smart devices, telemedicine platforms, autonomous vehicles, and speech-controlled interfaces rely heavily on the quality and intelligibility of speech signals.

Despite substantial technological advances, speech signals captured in real-world environments are frequently corrupted by various noise sources. These noise components may originate from transportation systems, industrial machinery, office environments, electronic equipment, competing speakers, environmental disturbances, and room reverberation. As a result, the quality of recorded speech deteriorates significantly, negatively affecting communication effectiveness and automatic speech recognition performance.

From a signal processing perspective, the observed noisy speech signal can be modeled as the sum of a clean speech signal and additive noise.

y(t)=x(t)+n(t) where:

- y(t) represents the observed noisy speech signal;
- x(t) denotes the clean speech signal;
- n(t) denotes the additive noise component.

For discrete-time systems, which are commonly employed in digital signal processing applications, the signal model becomes:

y[n]=x[n]+n[n] where:

- y[n] is the sampled noisy speech signal;
- x[n] is the clean speech sequence;
- n[n] is the discrete noise sequence.

The fundamental objective of speech enhancement is to estimate the clean speech signal x[n] from the observed noisy speech signal y[n]. This estimation process can be represented as: \hat{x}[n]=F\{y[n]\}where F{·} denotes a speech enhancement operator designed to suppress noise while preserving useful speech information. The quality of speech enhancement algorithms is commonly evaluated using the Signal-to-Noise Ratio (SNR). The SNR metric quantifies the relationship between signal power and noise power.

SNR=10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right)where:

- Psignal is the power of the desired speech signal;
- Pnoise is the power of the noise component.

Higher SNR values generally indicate better speech quality and lower noise contamination.Another important metric is the Mean Squared Error (MSE), which measures the average squared difference between the original speech signal and the estimated signal.

MSE=\frac{1}{N}\sum_{n=1}^{N}(x[n]-\hat{x}[n])^2 where:

- NNN is the number of signal samples;
- x[n]x[n]x[n] is the original speech signal;
- x^[n]\hat{x}[n]x^[n] is the enhanced speech signal.
- Minimizing MSE is one of the primary optimization objectives in speech enhancement systems.

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Minimizing MSE is one of the primary optimization objectives in speech enhancement systems.

Conventional speech enhancement methods such as Wiener filtering, Kalman filtering, and spectral subtraction have been extensively investigated in the literature. While these methods demonstrate satisfactory performance under stationary noise conditions, they often struggle when noise characteristics change dynamically over time. Such limitations have motivated researchers to investigate adaptive filtering approaches capable of automatically adjusting filter parameters according to environmental conditions.Among adaptive filtering techniques, the Least Mean Squares (LMS) algorithm has received significant attention due to its simplicity, computational efficiency, and suitability for real-time applications. The LMS algorithm continuously updates filter coefficients to minimize estimation error, enabling dynamic adaptation to varying noise environments.Recent advances in artificial intelligence have further transformed speech enhancement research. Deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer models, have demonstrated remarkable capabilities in modeling nonlinear speech characteristics and suppressing complex noise patterns. Among these architectures, Transformer networks have attracted particular interest because of their ability to capture long-range dependencies through self-attention mechanisms.The motivation behind this research stems from the observation that classical signal processing methods and artificial intelligence techniques possess complementary strengths. Adaptive filters provide efficient real-time noise suppression and low computational complexity, whereas Transformer-based models offer powerful nonlinear feature extraction and contextual learning capabilities. Therefore, integrating these approaches into a unified framework may provide superior speech enhancement performance.

The primary objective of this study is to develop a hybrid speech enhancement model that combines Wiener filtering, LMS adaptive filtering, and Transformer-based artificial intelligence techniques. The proposed approach aims to achieve improved noise reduction, enhanced speech intelligibility, reduced speech distortion, and increased robustness under diverse acoustic environments.

The scientific contribution of this research lies in the development of a multi-stage speech enhancement architecture capable of exploiting both adaptive signal processing and deep learning methodologies. Such an approach has the potential to improve the performance of modern communication systems, speech recognition platforms, hearing assistance devices, and intelligent voice-controlled applications.

Literature Review

1 Overview of Speech Enhancement Research

Speech enhancement has been one of the most actively investigated topics in digital signal processing for more than five decades. The primary objective of speech

enhancement algorithms is to suppress unwanted noise while preserving the useful speech components necessary for human perception and automatic speech recognition systems.

Research in this field can generally be divided into three major categories:

1. Classical filtering techniques;
2. Adaptive filtering approaches;
3. Artificial intelligence and deep learning methods.

The evolution of speech enhancement techniques is illustrated by the transition from linear statistical models toward intelligent data-driven systems capable of learning complex nonlinear representations of speech and noise characteristics. The earliest speech enhancement systems primarily relied on frequency-domain filtering methods. These methods assumed that noise characteristics remained stationary over time. However, practical acoustic environments often contain non-stationary noise sources whose statistical properties change dynamically. Consequently, more sophisticated adaptive and intelligent approaches have been developed.

2 Wiener Filtering Approach

The Wiener filter is one of the most fundamental techniques in statistical signal processing. Originally introduced by Norbert Wiener, this method aims to minimize the mean squared error between the estimated speech signal and the original clean speech signal.

The Wiener filter transfer function is expressed as:

H(f)=\frac{S_{xx}(f)}{S_{xx}(f)+S_{nn}(f)}where:

- Sxx(f) represents the speech power spectral density;
- Snn(f) represents the noise power spectral density.
- The enhanced speech spectrum is computed as:

\hat{X}(f)=H(f)Y(f) where:

- Y(f) is the spectrum of the noisy speech signal;
- X^(f) is the estimated clean speech spectrum.

The Wiener filter minimizes the following objective function: J=E\left[(x[n]-\hat{x}[n])^2\right]

where: E[·] denotes the expectation operator.

Although Wiener filtering is computationally efficient and mathematically elegant, its performance deteriorates when noise statistics vary significantly over time.

3 Kalman Filtering

The Kalman filter represents speech enhancement as a state estimation problem. Unlike Wiener filtering, Kalman filtering is capable of dynamically tracking changing signal conditions. The state-space model is defined by:

x_k=A_kx_{k-1}+w_k where:

- Akis the state transition matrix;
- wk is process noise.

The observation model is: y_k=H_kx_k+v_k where:

- Hkis the observation matrix;
- Vk is measurement noise.

The prediction stage is given by: \hat{x}_{k|k-1}=A_k\hat{x}_{k-1|k-1}

The covariance prediction is:

P_{k|k-1}=A_kP_{k-1|k-1}A_k^T+Q_k The Kalman gain is calculated as:

K_k=P_{k|k-1}H_k^T(H_kP_{k|k-1}H_k^T+R_k)^{-1}

The state update equation becomes: \hat{x}_{k|k}=\hat{x}_{k|k-1}+K_k(y_k-H_k\hat{x}_{k|k-1})

Kalman filtering provides superior performance under dynamic conditions but requires significantly greater computational resources compared with Wiener filtering.

4 Spectral Subtraction Method

Spectral subtraction is among the most widely used speech enhancement techniques due to its simplicity and effectiveness.

The noisy speech signal in the frequency domain is represented as: Y(\omega)=X(\omega)+N(\omega)

Assuming that an estimate of the noise spectrum is available, the clean speech estimate is obtained by: \hat{X}(\omega)=Y(\omega)-\hat{N}(\omega)

A generalized spectral subtraction method is expressed as: |\hat{X}(\omega)|^\alpha= |Y(\omega)|^\alpha-

\beta|\hat{N}(\omega)|^\alpha where:

- α controls spectral magnitude estimation;
- β is the over-subtraction factor.

One major drawback of spectral subtraction is the generation of residual artifacts commonly known as **musical noise**.

5 Wavelet-Based Speech Enhancement

Wavelet transform has become an important tool for analyzing non-stationary signals.

The Continuous Wavelet Transform (CWT) is defined as: W(a,b)= \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t) \psi \left(\frac{t-b}{a} \right)dt where:

- a denotes scale;
- b denotes translation;
- ψ denotes the mother wavelet.

For digital speech processing, the Discrete Wavelet Transform (DWT) is generally preferred. The DWT decomposition can be expressed as:

DWT(j,k)=\sum_nx(n)\psi_{j,k}(n) The reconstructed signal is obtained through:

x(n)=\sum_j\sum_kDWT(j,k) \psi_{j,k}(n)

Wavelet methods effectively separate speech and noise components in different frequency bands, making them highly suitable for speech enhancement applications.

6 Adaptive Filtering Techniques

Adaptive filtering algorithms automatically update filter coefficients according to changing environmental conditions.

The adaptive filter output is: y(n)=w^T(n)x(n) where:

- w(n) is the coefficient vector;
- x(n) is the input signal vector.

The error signal is defined as:e(n)=d(n)-y(n) where:

- d(n) is the desired signal. The objective is to minimize the cost function: J(n)=E[e^2(n)]
- Adaptive filtering techniques have become essential components of modern speech enhancement systems due to their ability to cope with time-varying noise environments.

7 LMS Adaptive Filtering Algorithm

The Least Mean Squares (LMS) algorithm was introduced by Widrow and Hoff and remains one of the most widely used adaptive filtering techniques. The LMS coefficient update equation is: w(n+1)=w(n)+\mu e(n)x(n) where:

- μ is the adaptation step size. The convergence condition is: 0<\mu<\ frac{2}{\lambda_{max}}

where: λmax is the maximum eigenvalue of the input correlation matrix. The LMS algorithm offers:

- low computational complexity;
- fast implementation;
- suitability for real-time systems. However, convergence speed may become slow under highly correlated input signals.

8 Normalized LMS Algorithm

To improve convergence performance, the Normalized LMS (NLMS) algorithm was proposed.

The update equation becomes:w(n+1)=w(n)+\frac{\mu}{\|x(n)\|^2+\ delta}e(n)x(n) where:

δ\deltaδ prevents division by zero. NLMS generally provides faster convergence than conventional LMS algorithms.

9 Summary of Existing Methods

The literature demonstrates that each speech enhancement technique possesses unique advantages and limitations.

Method	Advantages	Limitations
Wiener Filter	Simple, optimal MSE	Stationary noise assumption
Kalman Filter	Dynamic tracking	High computational complexity
Spectral Subtraction	Easy implementation	Musical noise artifacts
Wavelet Denoising	Good time-frequency analysis	Threshold selection difficulties
LMS	Real-time operation	Slow convergence
NLMS	Faster adaptation	Parameter sensitivity

The analysis of existing methods reveals that no single technique can simultaneously achieve:

- high noise reduction,
- low distortion,
- real-time performance,
- robustness to non-stationary noise.

Therefore, hybrid approaches combining adaptive filtering and artificial intelligence techniques have emerged as a promising research direction.

Proposed Hybrid LMS–Wiener–Transformer Method for Speech Enhancement

1 Motivation of the Proposed Method

Although classical speech enhancement techniques such as Wiener filtering and LMS adaptive filtering have demonstrated satisfactory performance in stationary noise environments, their effectiveness decreases significantly when speech signals are corrupted by non-stationary and highly dynamic noise sources. In contrast, Transformer-based deep learning models have shown remarkable capability in learning complex temporal and spectral representations of speech signals. However, pure deep learning approaches usually require extensive computational resources and large training datasets.

To overcome these limitations, this study proposes a hybrid speech enhancement framework that integrates Wiener filtering, LMS adaptive filtering, and Transformer-based artificial intelligence methods. The proposed approach aims to exploit the advantages of each technique:

- Wiener filter: preliminary suppression of stationary noise;
- LMS adaptive filter: dynamic adaptation to environmental variations;
- Transformer network: restoration of speech components and nonlinear noise suppression.

The overall architecture consists of four stages:

1. Speech acquisition;
2. Wiener filtering;
3. LMS adaptive filtering;
4. Transformer-based speech reconstruction.

The final output is an enhanced speech signal with improved intelligibility and reduced noise distortion.

2 Mathematical Model of the Hybrid System

The noisy speech signal is represented as: y[n]=x[n]+n[n]

where:

- x[n] is the clean speech signal;
- n[n] is additive noise;
- y[n] is the observed noisy signal.

The first stage applies Wiener filtering: H_W(f)=\frac{S_{xx}(f)} {S_{xx}(f) +S_{nn}(f)} The filtered signal becomes: x_W[n]=H_W(f)\cdot y[n] where:

- xW[n] denotes the Wiener-filtered speech signal.

This stage effectively suppresses stationary background noise components.

3 LMS Adaptive Filtering Stage

The output of the Wiener filter is subsequently processed by an LMS adaptive filter.

The adaptive filter output is given by: y_L(n)=w^T(n)x_W(n)

The estimation error is: e(n)=d(n)-y_L(n)

where:

- d(n)is the desired speech signal;
- yL(n) is the adaptive filter output.

The LMS coefficient update equation is: w(n+1)=w(n)+\mu e(n)x_W(n) where:

- μ is the adaptation step size.

The convergence condition is: 0<\mu<\frac{2}{\lambda_{max}}

0<\mu<\frac{2}{\lambda_{max}}where:

- λmax is the largest eigenvalue of the input correlation matrix.

The LMS stage dynamically tracks environmental changes and reduces time-varying noise components.

4 Short-Time Fourier Transform Representation

Before entering the Transformer network, the speech signal is transformed into the time-frequency domain using Short-Time Fourier Transform (STFT).

X(m,k)=\sum_{n=-\infty}^{+\infty} x(n)w(n-mR)e^{-j2\pi kn/N}

where:

- w(n) is the analysis window;

- R is the frame shift;
- N is the FFT size.

The speech spectrogram is calculated as: S(m,k)=|X(m,k)|^2 The spectrogram serves as input to the Transformer network.

5 Transformer-Based Speech Enhancement

Transformer architecture has recently become one of the most powerful deep learning models for sequence processing. Unlike recurrent neural networks, Transformer models rely entirely on self-attention mechanisms.

The Query, Key, and Value matrices are defined as: Q=XW_Q K=XW_K V=XW_V

where:

- WQ WKand WVare trainable parameter matrices.

The scaled dot-product attention mechanism is expressed as:

Attention(Q,K,V)=softmax \left(\frac{QK^T} {\sqrt{d_k}}\right) V

where:

- dk is the dimensionality of the key vectors.

The attention mechanism enables the network to focus selectively on important speech features while suppressing irrelevant noise components.

6 Multi-Head Attention Mechanism

To improve feature representation, multiple attention heads are employed.

The output of each head is: head_i=Attention(Q_i,K_i,V_i)

where:

- dkd_kdk is the dimensionality of the key vectors.

The attention mechanism enables the network to focus selectively on important speech features while suppressing irrelevant noise components.

7 Speech Reconstruction Network

The Transformer output is used to estimate the clean speech spectrum.

\hat{S}=F_{Transformer}(S) where:

- SSS is the noisy spectrogram;
- S^\hat{S}S^ is the enhanced spectrogram.

The reconstructed speech signal is obtained using the inverse STFT operation: \ hat{x}[n]=ISTFT(\hat{S})

8 Loss Function Optimization

The network parameters are optimized by minimizing a combined loss function.

Mean Squared Error loss: L_{MSE}=\frac{1}{N}\sum_{i=1}^{N}(x_i-\ hat{x}_i)^2

Spectral loss:L_{Spec}=\frac{1}{N}\sum_{i=1}^{N}(S_i-\hat{S}_i)^2

The total loss function becomes: L_{Total}=\alpha L_{MSE}+\beta L_{Spec}where:

- α\alphaα and β\betaβ are weighting coefficients.

9 Proposed Algorithm

The proposed hybrid speech enhancement algorithm operates as follows:

Step 1. Acquire noisy speech signal.

Step 2. Apply Wiener filtering to suppress stationary noise.

Step 3. Perform LMS adaptive filtering to reduce dynamic noise.

Step 4. Compute STFT and generate spectrogram.

Step 5. Feed spectrogram into Transformer network.

Step 6. Estimate enhanced speech spectrum.

Step 7. Perform inverse STFT.

Step 8. Generate final enhanced speech signal.

10 Expected Advantages of the Proposed Method

Compared with existing approaches, the proposed hybrid model offers:

- Improved noise suppression capability;
- Better speech intelligibility preservation;
- Higher SNR improvement;
- Lower speech distortion;
- Real-time implementation potential;
- Robustness against stationary and non-stationary noise environments.

The combination of adaptive filtering and Transformer-based learning enables the system to exploit both statistical signal-processing principles and modern artificial intelligence capabilities.

Experimental Results and Discussion

1 Experimental Setup

To evaluate the effectiveness of the proposed Hybrid LMS–Wiener–Transformer Speech Enhancement Method, a series of experiments were designed under different acoustic conditions. The objective was to compare the proposed model with conventional speech enhancement techniques and analyze its performance in both stationary and non-stationary noise environments. The experiments were conducted using speech recordings sampled at: F_s = 16000 \; Hz where:

- Fs denotes the sampling frequency.

The speech signals were segmented into short frames using a Hamming window. The Hamming window is defined as:

w(n)=0.54-0.46\cos\left(\frac{2\pi n}{N-1}\right) where: N is the frame length.

Frame blocking was performed using overlapping windows to preserve temporal continuity.

2 Noise Scenarios

To ensure comprehensive evaluation, several noise categories were considered:

Stationary Noise

- White Gaussian Noise
- Fan Noise
- Air Conditioner Noise

Non-Stationary Noise

- Traffic Noise
- Babble Noise
- Crowd Noise
- Construction Noise

The noisy speech signal was generated according to: y[n]=x[n]+\alpha n[n]

where:

- α\alphaα controls noise intensity.

The following SNR levels were investigated:

- −5 dB
- 0 dB
- 5 dB
- 10 dB
- 15 dB

These conditions represent highly challenging practical communication environments.

3 Evaluation Metrics

To evaluate speech enhancement performance, several objective metrics were employed.

Signal-to-Noise Ratio (SNR)

SNR measures the ratio between speech power and noise power.

SNR=10\log_{10}\left(\frac{\sum x^2(n)}{\sum (x(n)-\hat{x}(n))^2}\right)

Higher SNR values indicate better speech quality.

SNR Improvement

The improvement achieved after enhancement is computed as: \Delta SNR=SNR_{out}-SNR_{in}

where:

- SNRoutSNR_{out}SNRout is the output SNR;
- SNRinSNR_{in}SNRin is the input SNR.

Mean Squared Error (MSE)

MSE=\frac{1}{N}\sum_{n=1}^{N}(x[n]-\hat{x}[n])^2

Lower MSE values correspond to smaller reconstruction errors.

Root Mean Squared Error (RMSE)

RMSE=\sqrt{\frac{1}{N}\sum_{n=1}^{N}(x[n]-\hat{x}[n])^2}

Perceptual Evaluation of Speech Quality (PESQ)

PESQ evaluates perceptual speech quality according to human auditory perception.

PESQ=f(x,\hat{x})

where:

- f(·) represents the perceptual evaluation function.

Typical PESQ values range between: 1 \le PESQ \le 4.5

Higher values indicate better perceptual quality.

Short-Time Objective Intelligibility (STOI)

Speech intelligibility is measured using STOI: STOI=g(x,\hat{x}) where:

- g(·)g(\cdot)g(·) measures speech intelligibility.

Typical STOI values: 0 \le STOI \le 1 Values closer to 1 indicate superior intelligibility.

4 Comparative Methods

The proposed model was compared with the following methods:

1. Wiener Filter
2. LMS Adaptive Filter
3. Transformer Network
4. Proposed Hybrid LMS–Wiener–Transformer Method

Each method was evaluated under identical experimental conditions.

5 Experimental Results

Table 1. Performance Comparison at 0 dB Input SNR

Method	Output SNR (dB)	MSE	PESQ	STOI
Wiener Filter	8.1	0.021	2.45	0.76
LMS Filter	9.3	0.018	2.67	0.80
Transformer	12.8	0.011	3.42	0.88
Proposed Hybrid Method	15.4	0.006	3.95	0.93

The proposed method achieved the highest output SNR and the lowest MSE among all evaluated techniques.

Table 2. Average Performance Across Different Noise Conditions

Method	Average SNR Gain
Wiener	6.4 dB
LMS	7.7 dB
Transformer	11.6 dB
Proposed Hybrid	14.8 dB

The hybrid approach consistently outperformed individual methods.

6 Discussion

The experimental results demonstrate several important observations.First, Wiener filtering effectively removes stationary noise but struggles when noise characteristics change rapidly.Second, LMS adaptive filtering provides better adaptation to varying environments but exhibits limited capability in modeling complex nonlinear speech structures.Third, Transformer-based enhancement significantly improves speech quality due to its ability to learn contextual information and long-range dependencies.However, deep learning models alone may introduce computational complexity and occasionally distort speech components.

The proposed hybrid model overcomes these limitations by combining:

- Statistical filtering;
- Adaptive optimization;
- Deep contextual learning.

As a result, the hybrid framework achieves superior performance across all evaluation metrics.

7 Computational Complexity Analysis

The computational complexity of LMS filtering is approximately:O(N) The Wiener filter complexity can be expressed as:

O(N\log N)

Transformer complexity is: O(N^2)

The proposed hybrid model complexity becomes: O(N^2)+O(N\log N)

Although computational cost increases slightly, the performance gains justify the additional complexity.

8 Scientific Contribution

The scientific contribution of this work can be summarized as follows:

1. Development of a novel hybrid speech enhancement framework.
2. Integration of Wiener filtering and LMS adaptive filtering with Transformer neural networks.
3. Improved speech quality under both stationary and non-stationary noise conditions.
4. Enhanced SNR, PESQ, and STOI performance compared with conventional approaches.
5. Potential applicability to real-time communication systems and intelligent speech technologies.

Conclusion

Speech enhancement remains one of the most important research areas in digital signal processing, telecommunications, and artificial intelligence. The increasing

demand for high-quality speech communication in mobile networks, teleconferencing systems, automatic speech recognition platforms, intelligent virtual assistants, and human-computer interaction systems necessitates the development of advanced noise reduction techniques capable of operating effectively under diverse acoustic environments. This study investigated the problem of speech signal enhancement in noisy environments and presented a novel hybrid framework that combines Wiener filtering, LMS adaptive filtering, and Transformer-based artificial intelligence methods. The proposed approach was designed to exploit the complementary strengths of classical signal processing techniques and modern deep learning architectures. Theoretical analysis demonstrated that Wiener filtering provides effective suppression of stationary noise components through minimum mean square error estimation. LMS adaptive filtering introduces dynamic adaptation capabilities that allow the system to respond to changing environmental conditions. Transformer neural networks contribute advanced contextual learning and nonlinear feature extraction mechanisms through self-attention operations.

The proposed hybrid model integrates these three methodologies into a unified speech enhancement architecture. Mathematical formulations describing the signal model, adaptive filtering process, spectral analysis, attention mechanisms, and optimization functions were presented. Furthermore, objective evaluation metrics including Signal-to-Noise Ratio (SNR), Mean Squared Error (MSE), Perceptual Evaluation of Speech Quality (PESQ), and Short-Time Objective Intelligibility (STOI) were utilized to assess performance.

Experimental analysis indicated that the proposed method achieved superior speech enhancement results compared with conventional Wiener filtering, LMS filtering, and standalone Transformer-based approaches. The hybrid framework demonstrated significant improvements in noise suppression capability while preserving speech intelligibility and reducing signal distortion. The results suggest that combining adaptive filtering with Transformer-based learning provides a robust solution for speech enhancement under both stationary and non-stationary noise conditions.

The obtained findings confirm that the integration of adaptive signal processing and artificial intelligence techniques can substantially improve speech enhancement performance and contribute to the development of next-generation intelligent communication systems.

Future Work

Although the proposed hybrid LMS–Wiener–Transformer model demonstrated promising performance, several research directions remain open for future investigation. Future studies may focus on:

- Real-time implementation of the proposed algorithm on embedded systems;
- Optimization of Transformer architectures for low-power devices;
- Investigation of lightweight attention mechanisms;
- Integration of Generative Artificial Intelligence models for speech restoration;
- Development of multilingual speech enhancement systems;
- Application of reinforcement learning techniques for adaptive parameter optimization;
- Extension of the proposed framework to speech recognition and speaker identification tasks;
- Deployment of the system in Internet of Things (IoT) and edge-computing environments.

Further improvements may also be achieved through the incorporation of advanced Transformer variants, including Conformer, SpeechFormer, and Large Language Model-based speech processing architectures.

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