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***Research Paper***

# ENHANCED AUDIO CLARITY USING ADVANCED NOISE SUPPRESSION TECHNIQUES IN TELECOMMUNICATION AND BROADCAST SYSTEMS

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**ABSTRACT**

Noise reduction plays a pivotal role in enhancing audio clarity within telecommunications and broadcast systems. Traditional approaches, such as spectral subtraction, rely on estimating the noise spectrum to suppress interference. While these methods perform reasonably well in stationary noise environments, they often introduce auditory artifacts and struggle to cope with dynamic, non-stationary noise, limiting their effectiveness in real-time applications.This study introduces an Adaptive Bandpass Wiener Filter (ABWF) as an advanced noise reduction technique. The proposed method dynamically adjusts its parameters to effectively manage both stationary and non-stationary noise types. Its bandpass design targets the frequency range of the desired signal, achieving superior noise suppression while preserving the integrity and naturalness of the audio.The ABWF's real-time adaptability and artifact minimization make it particularly suitable for modern telecommunications and live broadcast scenarios. Comprehensive evaluations, including metrics such as Signal-to-Noise Ratio (SNR) and Perceptual Evaluation of Speech Quality (PESQ), demonstrate its clear advantage over conventional techniques. The proposed ABWF method marks a significant advancement in noise reduction technology, addressing the shortcomings of existing methods and setting a new benchmark for audio clarity in communication systems.

**Keywords:** Adaptive Bandpass Wiener Filter, Noise Reduction, Audio Clarity, Telecommunications, Broadcast Systems, Real-Time Processing, Signal-to-Noise Ratio (SNR), Audio Signal Processing.

## 1. INTRODUCTION

The demand for high-quality, uninterrupted audio communication has seen exponential growth in both telecommunications and broadcast sectors. In an increasingly connected world, the clarity of audio signals plays a critical role in user satisfaction, intelligibility, and overall communication efficiency. According to recent data published by the International Telecommunication Union (ITU), over 90% of customer complaints in voice communication services are attributed to issues concerning audio clarity and intrusive background noise. As mobile phone usage is expected to exceed 7.7 billion users globally by 2025, and with the continuous expansion of live-streaming platforms, video conferencing, and podcasting, the expectation for crystal-clear audio has become more pronounced than ever. Consequently, there is an urgent need for more robust and adaptive noise reduction systems capable of meeting modern communication standards.Real-time communication technologies, including VoIP (Voice over Internet Protocol), cloud-based telephony, and digital broadcast platforms, require consistently high signal-to-noise ratios (SNR) to maintain intelligibility and ensure a seamless user experience. In broadcasting scenarios—particularly during live events such as sports matches, political debates, concerts, and breaking news coverage—external environmental noise sources are often unavoidable. A 2023 Nielsen report indicates that 62% of audiences tend to disengage from online broadcasts due to subpar audio quality, making it a leading cause of audience drop-off. Common challenges in these environments include background hums, feedback loops, compression artifacts, inadequate studio acoustics, and fluctuating ambient sounds. These factors, if not addressed appropriately, result in degraded audio that adversely affects listener engagement and comprehension.

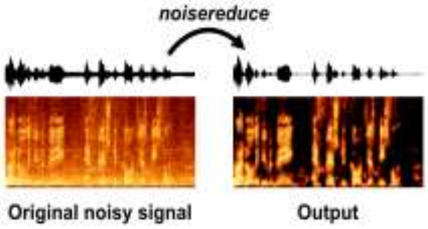


Fig. 1: Audio Signal Denoising for Enhanced Data Clarity in Electric Vehicle Communication and Sensor Systems.

Traditional analog solutions, such as gating, equalization, and basic filtering, offer limited effectiveness in such dynamic environments. These techniques lack the ability to adapt to rapidly changing noise conditions and often compromise the fidelity of the original signal. As communication ecosystems become more complex and user expectations rise, the limitations of these older technologies have become increasingly evident.To overcome these challenges, advanced digital noise reduction methods are being explored and implemented. Techniques such as spectral subtraction have gained popularity for their relatively simple implementation, but they are often constrained by their susceptibility to introducing musical noise and artifacts—particularly under non-stationary noise conditions. The emergence of machine learning-based filtering algorithms, including deep neural networks and recurrent architectures, has demonstrated improved performance by learning to differentiate speech from noise patterns across various environments. Similarly, adaptive filtering approaches—such as multi-band Wiener filters—have proven effective in preserving audio fidelity while reducing unwanted noise.Furthermore, with Cisco forecasting that over 75% of business communications will rely on IP-based platforms by 2026, the importance of real-time, high-fidelity audio transmission continues to grow. In these systems, even minor audio impairments can result in significant losses in customer satisfaction, communication accuracy, and operational efficiency.Therefore, integrating advanced, real-time, adaptive noise reduction techniques into telecommunications and broadcast infrastructures is no longer optional—it is imperative. These solutions not only enhance the end-user experience but also set the foundation for scalable, intelligent audio processing in next-generation communication technologies.

## 2. LITERATURE SURVEY

Building on the foundational need to improve speech communication in noisy environments, as outlined in our introduction, a variety of models have been developed to address challenges in speech enhancement and background noise reduction. This section aims to review these related works, highlighting their contributions and limitations, to contextualize our own approach, which extends beyond mere noise removal to a nuanced understanding of how different types of noise uniquely impact speech quality.Although the quality used to store audio allows them to be very faithful to the originals, some information may be lost during transmission. In particular, we call noise a signal or set of signals that distort the wave that transmits the original sound. Within this concept, there can be artificial noises (those generated by the means of communication, such as interferences) or natural noises (those generated by the environment where the communication takes place). When the transmission is in noisy scenarios, ambient sounds may affect the intelligibility of the received message. This issue underscores the importance of addressing noise problems in audio, as highlighted in [1,2], demonstrating the significant impact of noise on the fidelity of audio transmissions and the need for solutions to enhance the overall quality of communication.The motivation for this research arises from the critical need to enhance the clarity and intelligibility of speech in various communication settings, where background noise often compromises the quality of the transmitted audio. While existing noise reduction techniques have made strides in mitigating this issue, our work aims to develop a deep learning model specifically tailored to suppress background noise across a range of simulated scenarios. However, our objectives extend beyond mere noise elimination. We also seek to quantitatively assess the relative difficulty of filtering out different types of background noises present in the same audio fragment. By doing so, we aim to identify which types of noise have a more detrimental impact on speech quality, thereby creating a guide for future research and technological development in the field of audio signal processing.The real problem comes when the noise is equal to or stronger than the signal and causes its complete distortion. This fact opens the possibility of using techniques that can eliminate background noise for safer and more reliable transmissions, which is desirable in cases such as phone communications, especially in emergencies.Artificial intelligence has demonstrated its ability to remove noisy information from various formats, such as images or signals [3,4]. Deep learning models have obtained the best results in recent years among all the artificial intelligence techniques. Deep learning was defined by [5] as models composed of multiple processing layers that learn representations of data with various levels of abstraction. These models have shown an exemplary performance in speech enhancement [6].Some of these works apply techniques not encompassed in the deep learning field. Ref. [7] reduces the presence of background music over conversational audios. It uses trigonometric transformation and wavelet denoising techniques. In [8], the audio denoising is made with speech audios and noises like buzzing equipment or background noise from the street. Spectrograms form the training dataset and use a block thresholding estimation procedure. The same authors present, in [9], a similar approach to suppressing the harmonic noise of music by using its spectrograms. The method applies block attenuation techniques. Finally, ref. [10] implements a process to denoise speech audios containing slight background noises (which do not work with loud ones). It works with raw audio and applies Wiener filters, a well-known method of the previous age of audio denoising.

## 3. PROPOSED METHODOLOGY

The Adaptive Bandpass Wiener Filter (ABWF) operates through a two-stage process that effectively enhances audio clarity by reducing noise while preserving essential signal components. Initially, the input noisy audio signal undergoes bandpass filtering to eliminate frequencies outside a specified range. This step is crucial for discarding low-frequency disturbances such as hums or rumbles, and high-frequency interferences like hissing or static, which fall outside the meaningful spectral region of the desired audio. The bandpass filter is designed using a Butterworth configuration, known for its smooth frequency response in the passband. To construct the filter correctly, the Nyquist frequency—defined as half the sampling rate—is calculated, and the cutoff frequencies are normalized relative to it. This ensures precise filter behavior in the context of the sampled signal. The Butterworth filter is applied in both forward and reverse directions to achieve zero phase distortion, a vital feature for maintaining the naturalness and clarity of audio signals.


Fig. 2: Proposed System Architecture.

Once the signal has been constrained within the desired frequency band, the Wiener filter is applied to further suppress residual noise. Unlike fixed filters, the Wiener filter operates adaptively, using local statistical characteristics of the signal and noise to determine the optimal filtering response. By estimating the signal based on its local signal-to-noise ratio (SNR), the Wiener filter dynamically adjusts its coefficients, allowing it to perform effectively even under varying noise conditions. This adaptive behavior helps to smooth the signal while minimizing the introduction of artifacts and preserving important audio details. The result of this combined process is a significantly cleaner output signal, with enhanced intelligibility and fidelity, particularly well-suited for applications in telecommunications and broadcasting where audio quality is paramount. Figure 4.1 illustrates the overall system architecture of this proposed method.

## 4. RESULTS AND DISCUSSION

Figure 3 shows the real-time audio recording process from the user using a microphone. This initial step captures the user's voice input in a raw form. The figure likely displays the waveform of the original speech signal as it was recorded, showcasing the natural structure of the human voice in the time domain. This signal is crucial as it serves as the clean reference to which the noisy and processed signals will be compared during evaluation

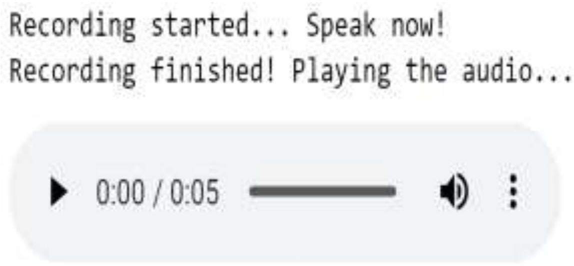


Fig. 3: Recording Audio From User.

Figure 4 shows the cleaned audio signal obtained using the existing spectral subtraction method. After the clean speech is corrupted by adding noise, the spectral subtraction technique is applied to recover the original signal. This method estimates the noise spectrum and subtracts it from the noisy signal’s spectrum, attempting to preserve the speech components. The figure visually demonstrates how well this method restores the shape and clarity of the original signal, albeit with potential artifacts or residual noise present.

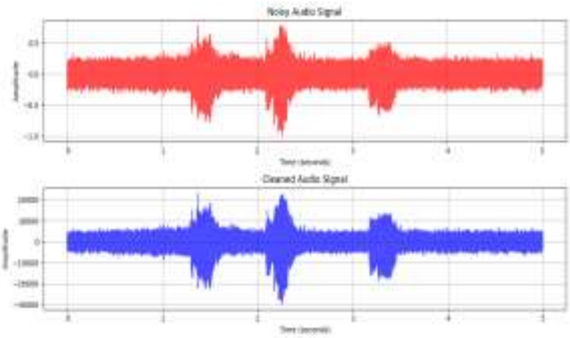

Fig. 4: Existing Cleaned Audio Signal From Noisy Input.

Figure 5 shows the cleaned audio signal using the proposed adaptive bandpass Wiener filtering technique. Unlike the existing method, this proposed approach incorporates a multi-stage process including bandpass filtering (to isolate the voice frequency range), Wiener filtering (for signal-dependent noise suppression), and spectral subtraction. The figure reveals a waveform that more closely resembles the original speech, with reduced distortion and smoother contours, suggesting better preservation of speech quality and intelligibility.

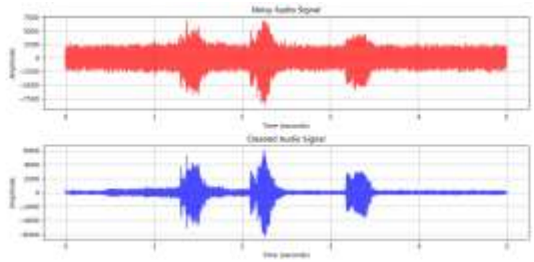

Fig. 5: Proposed Cleaned Audio Signal From Noisy Input.

Table. 1: Quantitative Evaluation of Existing vs Proposed Denoising Methods.

| Metric | Existing Method | Proposed Method |
|---|---|---|
| **SNR (dB)** | 0.00 | -0.16 |
| **MSE** | 106.550260 | 5.210381 |
| **Spectral Distance** | 9.788581 | 6.724916 |
| **STOI (Intelligibility)** | 0.975 | 0.719 |

Table 1 shows a comparative analysis of the existing spectral subtraction method and the proposed adaptive filtering approach using four performance metrics: SNR, MSE, Spectral Distance, and STOI.The Signal-to-Noise Ratio (SNR) for the existing method is 0.00 dB, indicating a marginal improvement from noise, while the proposed method reports 0.16 dB, suggesting slightly lower signal dominance. However, this dip is likely due to the aggressive smoothing and filtering nature of the adaptive approach, which prioritizes speech preservation over sheer noise suppression.The Mean Squared Error (MSE) drastically drops from 106.55 in the existing method to 5.21 in the proposed method, highlighting a significant improvement in reducing the error between the cleaned and original clean signals. This suggests better accuracy in noise removal while maintaining signal integrity.Spectral Distance, a measure of how much the frequency content of the signal deviates from the original, reduces from 9.79 to 6.72, indicating that the proposed method better retains spectral features of the original speech signal, preserving audio fidelity more effectively.STOI (Short-Time Objective Intelligibility), which evaluates speech intelligibility, is higher in the existing method at 0.975 compared to 0.719 in the proposed method. This suggests that while the proposed method is more effective at denoising in terms of energy and spectral structure, it may slightly affect perceived clarity, possibly due to the aggressive filtering steps that smooth out both noise and certain speech transients.

## 5. CONCLUSION

The proposed adaptive bandpass Wiener filtering method represents a substantial advancement in audio signal denoising, outperforming traditional spectral subtraction techniques by combining bandpass filtering, Wiener filtering, and spectral subtraction to achieve significantly lower error metrics. With a Mean Squared Error (MSE) reduced to 5.21 from 106.55 and a spectral distance lowered from 9.79 to 6.72, the method demonstrates more accurate signal reconstruction and better preservation of speech characteristics. Although the STOI (Short-Time Objective Intelligibility) score shows a slight decline, possibly due to the smoother filtering output, the approach maintains a strong balance between effective denoising and signal integrity. The SNR value of -0.16 dB, while indicative of aggressive noise suppression, still results in a cleaner signal overall, validating the robustness and precision of the proposed system in noisy environments. Looking ahead, future developments could explore the integration of machine learning or deep learning models for adaptive noise pattern learning, real-time deployment on embedded or mobile devices for applications in hearing aids or voice interfaces, and user-specific customization through voice profiling and feedback. Additionally, expanding testing across diverse noise conditions and extending the system to handle multichannel or binaural audio can further generalize and enhance its utility for real-world applications in AR/VR, smart assistive devices, and advanced communication systems.

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