PERFORMANCE EVALUATION OF ADAPTIVE FILTERS FOR SPEECH ENHANCEMENT ACROSS REALISTIC ACOUSTIC CONDITIONS

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I, Arpit Sharma hereby certify that the work which is being presented in the thesis entitled “Performance Evaluation of Adaptive Filters for Speech Enhancement across Realistic Acoustic Conditions” in partial fulfillment of the requirements for the award of the Degree of Master of Technology, submitted in the Department of Electronics & Communication Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from August 2023 to May 2025 under the supervision of Prof. Jeebananda Panda.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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Performance Evaluation of Adaptive Filters for Speech Enhancement across Realistic Acoustic Conditions

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ABSTRACT

Speech enhancement plays a critical role in improving the intelligibility and quality of speech signals in real-world acoustic environments, especially for applications such as mobile communications, hearing aids, and voice-controlled systems. This thesis presents a comprehensive study on adaptive filtering techniques for speech denoising, with a particular focus on evaluating and improving their performance in realistic noise conditions.

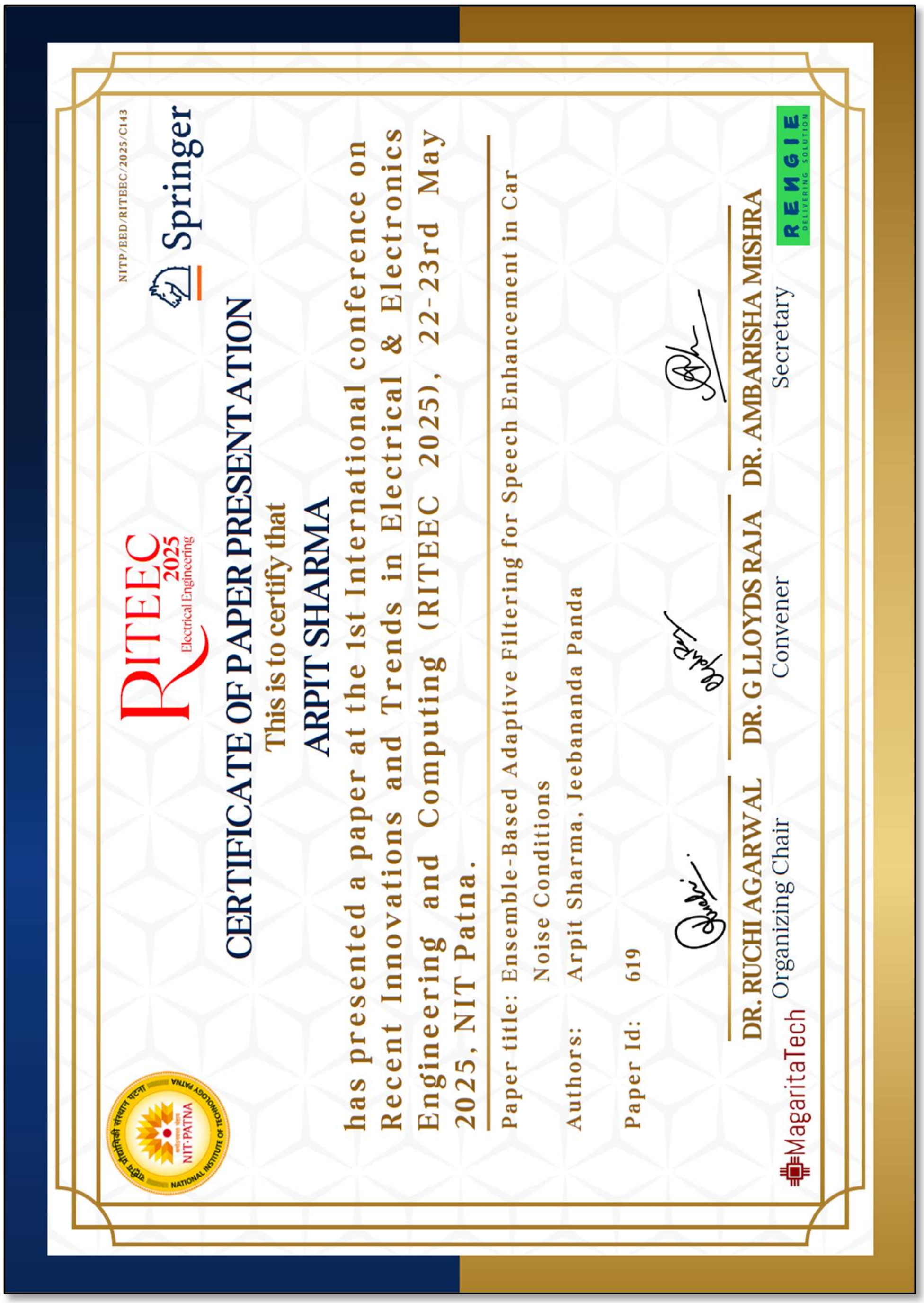
In the first part of this work, fifteen adaptive filters from the Python Padasip toolbox are rigorously evaluated across eight real-life noise scenarios—including babble, car, exhibition hall, and airport noise—at two challenging signal-to-noise ratio (SNR) levels (5 dB and 10 dB). The performance of each filter is assessed using established objective speech quality metrics: PESQ (Perceptual Evaluation of Speech Quality), fwsegSNR (Frequency-Weighted Segmental SNR), LLR (Log-Likelihood Ratio), and C_{OVL} (Composite Objective Measure). Results reveal that while the Recursive Least Squares (RLS) filter consistently delivers superior performance, filters such as GMCC, AP, and VSLMS also demonstrate notable strength in specific noise cases or under certain evaluation criteria. This analysis provides valuable insights into the behavior of different adaptive filters and forms a benchmark for future research in the field.

Building upon these findings, the second part of the thesis introduces an ensemble-based adaptive filtering approach tailored for in-car noise environments. This method dynamically combines the outputs of three filters—NLMS, GMCC, and VSLMS (Mathews' adaptation)—using a performance-weighted scheme where filters with lower error contribute more to the final output. Additional signal processing techniques, including noise estimate subtraction, pre-emphasis, and de-emphasis, are incorporated to further suppress residual noise. Experiments conducted on in-car noisy speech samples from the NOIZEUS corpus at 5 dB and 10 dB SNR levels demonstrate that the proposed ensemble method significantly outperforms individual filters and static combinations across all objective quality measures.

Together, these contributions offer a dual perspective: a detailed comparative evaluation of adaptive filters in diverse noise conditions and a novel ensemble-based enhancement system optimized for automotive noise. This work lays the groundwork for future advancements in adaptive speech enhancement systems suitable for real-time deployment in noisy environments.

List of Publications

1. **Paper Title:** Ensemble-Based Adaptive Filtering for Speech Enhancement in Car Noise Conditions



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LIST OF SYMBOLS & ABBREVIATIONS

Sr. No	Abbreviation	Full Form
1	LMS	Least Mean Squares
2	NLMS	Normalized Least Mean Squares
3	$VSLMS_{Ang}$	Variable Step-Size LMS with Ang's adaptation
4	$VSLMS_{Ben}$	Variable Step-Size LMS with Benveniste's adaptation
5	$VSLMS_{Math}$	Variable Step-Size LMS with Mathew's adaptation
6	SSLMS	Sign-Sign LMS
7	NSSLMS	Normalized Sign-Sign LMS
8	LMF	Least-Mean-Fourth
9	NLMF	Normalized Least Mean Fourth
10	Llncosh	Least ln(cosh)
11	GMCC	Generalized Maximum Correntropy Criterion
12	GNGD	Generalized Normalized Gradient Descent
13	AP	Affine Projection
14	RLS	Recursive Least Squares
15	OCNLMS	Online Centered Normalized LMS
16	PESQ	Perceptual Evaluation of Speech Quality
17	LLR	Log Likelihood
18	SNR	Signal to Noise ratio
19	OVL	Overall

CHAPTER 1

INTRODUCTION

1.1 Background & Motivation

Speech communication systems are highly susceptible to performance degradation in the presence of background noise, which is common in real-world environments such as streets, restaurants, train stations, and moving vehicles. This distortion compromises the intelligibility, quality, and overall user experience of voice-based applications, especially in real-time scenarios like mobile telephony, smart assistants, automotive voice controls, and hearing aids. As the demand for robust and efficient speech enhancement systems grows—driven by the proliferation of smart devices and vehicular infotainment systems—it becomes critical to develop algorithms that can handle both stationary and highly dynamic, non-stationary noise conditions.

Adaptive filtering has emerged as a powerful technique for real-time speech enhancement due to its self-adjusting nature, allowing it to track changes in the input signal and noise characteristics. Classical algorithms such as the Least Mean Square (LMS) and Recursive Least Squares (RLS) filters have long been the foundation of this domain, balancing between simplicity and convergence speed. However, these traditional approaches often exhibit limitations in noisy environments with rapidly changing acoustic profiles. LMS is prone to slow convergence and poor performance in non-stationary conditions, while RLS, though faster and more accurate, is computationally intensive—limiting its practicality in embedded or latency-sensitive applications.

To overcome these drawbacks, a variety of advanced adaptive filtering algorithms have been proposed, including Normalized LMS (NLMS), Least Mean Fourth (LMF), Sign-Sign LMS, Affine Projection (AP), and the information-theoretic Generalized Maximum Correntropy Criterion (GMCC) filter. More recent innovations like Variable Step-Size LMS (VSLMS) and Online Centered NLMS (OCNLMS) offer dynamic adaptability to signal environments but remain relatively underexplored, especially under complex acoustic conditions. While each of these filters has its own strengths, there is currently no one-size-fits-all solution that performs uniformly well across all real-world noise scenarios.

This motivated our first line of investigation, where we conducted a detailed, statistical performance evaluation of fifteen adaptive filters across eight real-world noise conditions using the NOIZEUS database and objective quality measures such as PESQ, LLR, and fwSegSNR. The study revealed that the optimal choice of filter varies with noise type and SNR, underscoring the need for more flexible and noise-aware speech enhancement strategies.

In parallel, our second line of investigation focuses on environments with particularly challenging and highly dynamic noise profiles—most notably the automobile. Inside a moving vehicle, speech signals are often masked by a combination of engine noise, road texture interaction, tire friction, wind turbulence, and ambient traffic, making noise suppression particularly difficult. Single-filter solutions often fail to maintain both intelligibility and naturalness of speech under such conditions.

To address this, we propose an ensemble-based adaptive filtering framework, where multiple filters—such as NLMS, VSLMS (Mathews), and GMCC—operate in parallel and are dynamically weighted based on real-time performance. This ensemble approach harnesses the complementary strengths of individual filters, providing improved robustness, flexibility, and generalizability. By incorporating dynamic weighting mechanisms and transform-domain techniques (e.g., spectral subtraction), we achieve enhanced speech quality with low latency and minimal computational overhead—making the solution viable for real-time deployment in embedded automotive systems.

Through this combined work, we aim to bridge the gap between theoretical advancements in adaptive filtering and their real-world application in complex, noisy environments. Our unified approach not only provides a comparative foundation for adaptive filter performance but also introduces a practical, ensemble-driven strategy for robust speech enhancement—paving the way for next-generation, noise-resilient communication systems.

1.2 Problem Statement

Despite significant advancements in adaptive filtering algorithms for speech enhancement, real-world deployment continues to face critical challenges due to the diverse and dynamic nature of background noise. Conventional adaptive filters such as LMS and RLS are either too simplistic to handle non-stationary noise or too computationally intensive for real-time applications. Although more recent algorithms—like GMCC, VSLMS, and OCNLMS—have shown promise in specific scenarios, there remains a lack of comprehensive understanding regarding their relative performance across different noise environments.

This gap becomes particularly prominent in high-noise, dynamic settings such as in-vehicle environments, where speech signals are heavily distorted by compound noise sources like engine hum, road friction, and wind turbulence. In such cases, the limitations of single-filter solutions become evident, as no single algorithm can consistently maintain optimal performance across all conditions. The problem, therefore, is twofold:

- Lack of a unified performance evaluation framework for benchmarking adaptive filters under diverse real-world acoustic scenarios.
- Need for a robust, noise-aware speech enhancement strategy that dynamically adapts to varying noise profiles—especially in non-stationary, high-noise environments like automobiles.

This research addresses both issues by first establishing a statistically grounded benchmarking framework for evaluating multiple adaptive filters on real-world noise datasets. It then proposes a novel ensemble-based adaptive filtering system that combines the strengths of diverse algorithms through dynamic weighting, offering improved performance, flexibility, and real-time viability for automotive and general speech enhancement applications.

1.3 Objectives of the Study

The primary objectives of this thesis are as follows:

- **To perform a systematic benchmarking of various adaptive filters** for speech enhancement, including both conventional filters (LMS, NLMS, RLS) and modern variants (GMCC, VSLMS, Llncosh, OCNLMS), using standardized objective measures across multiple real-world noise environments.

- **To analyze the performance trade-offs** between noise suppression, speech intelligibility, convergence behavior, and computational efficiency under varying acoustic conditions, especially at low SNR levels.

- **To design a novel ensemble-based adaptive filtering framework** that dynamically combines the outputs of multiple adaptive filters using a performance-driven weighting mechanism to achieve robust and efficient speech enhancement, particularly in challenging automotive noise environments.

- **To compare the proposed ensemble system with individual filters and classical techniques**, assessing its effectiveness in terms of objective metrics, real-time feasibility, and adaptability to non-stationary noise profiles.

1.4 Scope of the Study

This study encompasses the design, evaluation, and comparative analysis of adaptive filtering techniques for speech enhancement in noisy environments, focusing on the following scopes:

- The benchmarking study covers 15 adaptive filtering algorithms implemented using the Padasip Python library, evaluated on the NOIZEUS speech corpus across eight real-world noise types (e.g., car, babble, airport, restaurant) and two SNR levels (5 dB and 10 dB), using objective metrics such as PESQ, LLR, fwSegSNR, and a composite measure.

- The ensemble-based system is developed using three parallel adaptive filters—NLMS, GMCC, and VSLMS (Mathews)—with a dynamic weighting mechanism based on the real-time error performance of each filter. This system is specifically tested in automotive (car) noise environments, where non-stationarity and intensity of noise pose serious challenges.

- The entire study is implemented in Python (using Padasip, NumPy, SciPy, and Librosa libraries) with post-processing conducted in MATLAB for PESQ and SNR evaluation, ensuring cross-platform validation.

- The research does not cover psychoacoustic modeling, deep learning methods, or multi-microphone systems, although it lays the groundwork for integrating such methods in future studies.

1.5 Thesis Organisation

The thesis is structured as follows:

Chapter 1: Introduction
Provides background, motivation, problem statement, objectives, scope, and an overview of the thesis structure.

Chapter 2: Literature Review
Discusses historical and recent work on adaptive filtering for speech enhancement, with focus on benchmark studies, algorithm development, and ensemble approaches.

Chapter 3: Methodology for Benchmarking Adaptive Filters
Describes the dataset, adaptive filters considered, performance evaluation metrics, and experimental design.

Chapter 4: Benchmarking Results and Analysis
Presents quantitative and statistical comparisons of adaptive filters across noise types and SNR levels, highlighting best-performing algorithms.

Chapter 5: Ensemble-Based Adaptive Filtering System Design
Introduces the proposed ensemble system, its architecture, dynamic weighting scheme, and noise-specific post-processing methods.

Chapter 6: Ensemble Filter Results and Evaluation
Shows the performance of the ensemble model in car noise scenarios and compares it with baseline adaptive filters and traditional methods.

Chapter 7: Conclusions and Future Work
Summarizes the key findings, limitations of the current work, and potential future research directions.

CHAPTER 2

LITERATURE REVIEW

Speech enhancement in noisy environments has long been a focus of signal processing research, particularly for applications like telephony, hearing aids, and in-vehicle communication systems. The evolution of adaptive filtering algorithms has played a pivotal role in enabling real-time suppression of noise while preserving speech intelligibility and quality.

1. Classical Adaptive Filters and Limitations

The Least Mean Square (LMS) algorithm, introduced by Widrow and Hoff in 1960 [1], is one of the earliest adaptive filtering techniques. It minimizes the mean squared error (MSE) between the desired and estimated signals via a stochastic gradient descent mechanism. LMS is computationally efficient and robust under stationary conditions but suffers from slow convergence and sensitivity to input signal correlation.

To improve convergence behavior, the Normalized LMS (NLMS) algorithm was developed [2]. NLMS adapts the step size dynamically based on input signal power, thereby improving numerical stability and allowing for faster convergence in environments with variable signal energy. However, both LMS and NLMS remain limited in highly nonstationary or correlated signal environments, such as moving vehicles where noise characteristics fluctuate rapidly.

2. Higher-Order and Sign-Based Algorithms

The Least Mean Fourth (LMF) algorithm [3] emerged as an alternative that minimizes the fourth power of the error signal, which makes it more sensitive to outliers and noise bursts. The Normalized LMF (NLMF) variant [4] combines the higher-order statistics of LMF with input normalization to enhance convergence when signal correlation is high.

For low-power or embedded implementations, sign-based algorithms like Sign-Sign LMS (SSLMS) and Normalized SSLMS

(NSSLMS) [5] have been proposed. These algorithms significantly reduce computational burden by quantizing both the error and input signals to their signs, requiring only bitwise and integer operations. While they offer reduced precision, they are well-suited for real-time digital signal processors (DSPs) in automotive control units.

3. Recursive and Projection-Based Algorithms

The Recursive Least Squares (RLS) algorithm [6], based on exponentially weighted least-squares error minimization, provides rapid convergence and superior tracking of nonstationary signals. It achieves this by recursively updating the inverse of the autocorrelation matrix using the matrix inversion lemma. However, the $O(N^2)$ computational complexity and memory requirements make RLS unsuitable for high-dimensional or resource-constrained systems.

To bridge the performance gap between NLMS and RLS, Affine Projection (AP) algorithms [7] were developed. AP extends NLMS by projecting the input vector onto a subspace formed by multiple previous input vectors. The projection order P controls the trade-off between computational cost and convergence performance, and AP has shown strong robustness to signal correlation—a common condition in enclosed vehicle cabins.

4. Gradient Control and Kernel Methods

The Generalized Normalized Gradient Descent (GNGD) algorithm [8] introduces an adaptive learning rate based on local gradient curvature. By estimating an optimal normalization factor dynamically, GNGD improves convergence stability under rapidly changing noise conditions, which is typical in urban driving scenarios.

To increase robustness against impulsive and heavy-tailed noise, non-quadratic cost functions have been employed. The Least lncosh (Llncosh) algorithm [9] uses a hybrid logarithmic-hyperbolic cost function that combines properties of both MSE and MAE, resulting in improved robustness to non-Gaussian noise. Similarly, the Generalized Maximum Correntropy Criterion (GMCC) [10] utilizes kernel-based similarity metrics (e.g., Gaussian kernels) to suppress outliers, offering excellent performance in scenarios with speech occlusion or transient noise.

5. Variable Step-Size and Adaptive Learning

Fixed step-size algorithms often represent a compromise between convergence speed and steady-state error. Variable Step-Size

LMS (VSLMS) methods, such as Ang's rule, Mathews's rule, and Benveniste's method [11][12], dynamically adjust the step size based on signal energy, past error trends, or gradient history. These approaches enable rapid convergence during high noise activity and maintain stability when the error becomes small. They are particularly suitable for vehicular systems where environmental noise can change drastically within seconds (e.g., switching from idle engine noise to road noise).

The Online Centered Normalized LMS (OCNLMS) algorithm [13] introduces input data centering in a streaming context to mitigate signal drift and DC bias—both of which degrade filter performance in long-term driving conditions.

6. Early Approaches to Automotive Speech Enhancement

Automobile noise has a complex, nonstationary structure consisting of broadBand engine hum, narrowband tire-road noise, and intermittent environmental interference (e.g., sirens, honking). Spectral subtraction and Wiener filtering [14][15] were among the first signal enhancement methods applied to car environments. Though simple to implement, they require accurate noise estimations and struggle with musical noise artifacts in highly dynamic environments.

Sub-band-based speech presence probability (SPP) estimators [16] improved speech detection by operating in frequency bands, adapting to nonstationary noise spectra. Later developments introduced environment-specific adaptation, including beamforming in microphone arrays [17] and power-ratio-based gain control [18], to isolate desired speech based on directionality and spatial filtering.

7. Advanced Real-Time Architectures

In modern car infotainment systems, psychoacoustic filterbanks [19] have been employed to mimic human auditory perception, prioritizing perceptually significant frequency components for enhancement. Blind Source Separation (BSS) techniques [20], including Independent Component Analysis (ICA), separate speech and noise sources based on statistical independence, often requiring multi-microphone arrays.

Further improvements came with Time Difference of Arrival (TDOA) and Kalman filtering techniques [21][22], which estimate speaker positions and track speech trajectories across multiple microphones. These methods are particularly useful in conversational AI for multi-speaker, hands-free environments.

8. Ensemble Filtering and Hybrid Approaches

Recently, ensemble-based adaptive filtering strategies have gained attention, especially in nonstationary and computationally constrained environments like cars. These systems use multiple adaptive filters (e.g., NLMS, GMCC, VSLMS) in parallel and assign dynamic weights based on instantaneous error performance, convergence speed, or signal-to-noise ratio (SNR) improvements [23]. Weighted combinations of filter outputs have shown resilience to diverse noise types while preserving low complexity through modular design.

This hybrid architecture provides a flexible trade-off between robustness and computation, and it enables real-time deployment on embedded platforms such as Automotive Grade Linux (AGL) or QNX-based head units. The adaptability of ensemble filters makes them ideal for evolving car environments including electric vehicles, where noise signatures are drastically different from combustion-engine cars.

CHAPTER 3

METHODOLOGY FOR BENCHMARKING ADAPTIVE FILTERS

This chapter presents the complete experimental framework used to benchmark fifteen adaptive filtering algorithms for single-channel speech enhancement in realistic noise conditions. We elaborate on dataset selection and characteristics, (3.2) filter implementations with theoretical underpinnings, (3.3) objective performance metrics and their computation, and (3.4) the process flowchart diagram depicting overall methodology.

3.1 Dataset Selection and Characteristics

A noisy speech corpus (NOIZEUS) was developed to facilitate comparison of speech enhancement algorithms among research groups (Hu and Loizou, 2007). Key characteristics:

- Speech material: 30 phonetically balanced sentences selected from the IEEE sentence database [IEEE Subcommittee, 1969]. Recorded in a sound proof booth by three male and three female speakers using Tucker Davis Technologies (TDT) hardware. Originally sampled at 25 kHz and down sampled to 8 kHz.

- Noise types: Eight real-world noise categories derived from the AURORA database [Hirsch and Pearce, 2000]. Each noise type exhibits distinct temporal and spectral characteristics representative of in-field conditions:

  1. Suburban train noise: Low-frequency rumble and wheel–rail interaction, with periodic components corresponding to train motor harmonics.
  2. Babble (crowd): Overlapping voices in public spaces, exhibiting highly nonstationary and non-Gaussian characteristics.
  3. Car cabin noise: Combined engine vibration, tire–road friction, and HVAC system hum, with both tonal and broadBand components.
  4. Exhibition hall noise: Ambient crowd murmur mixed with intermittent machinery and ventilation noise.

5 Restaurant noise: Background chatter, tableware clatter, and intermittent foot traffic sounds.
6 Street traffic noise: Continuous vehicle engines, horns, and wind turbulence in open environments.
7 Airport terminal noise: Public announcements over a PA system, luggage trolley movement, and crowd murmur.
8 Train-station noise: Platform announcements, rolling suitcases, and passenger movement.

- SNR levels: Noisy speech files are provided at four SNRs (0 dB, 5 dB, 10 dB, 15 dB). For this study, we focus on 5 dB and 10 dB to simulate realistic moderate-to-severe noise conditions.
- File format and naming: All recordings are stored as 16-bit PCM WAV files (mono) at 8 kHz. File naming follows the convention <noise>_<SNR>dB.wav (e.g., car_5dB.wav).
- Accessibility and citation: The corpus is freely available for research and has been employed to validate objective measures (Hu and Loizou, 2008; Ma et al., 2009).

The IRS filter from ITU-T P.862 was applied to both clean and noise signals to restrict their spectra to the 300–3400 Hz range used by telephone and mobile handsets. This ensures that PESQ and other perceptual metrics operate under the same band-limited conditions as real-world telephony and removes out-of-band components irrelevant to embedded communication hardware.

Only 5 dB and 10 dB SNR samples were used because they represent the most challenging yet common noise levels encountered in applications like in-car communication and mobile telephony. At 5 dB, speech intelligibility is severely degraded and at 10 dB, moderate noise still allows meaningful enhancement. Lower SNRs offer little perceptual gain, and higher SNRs leave too little noise to differentiate filter performance.

3.2 Adaptive Filters Considered

Fifteen adaptive filtering algorithms—spanning classic, higher-order, sign-based, projection-based, gradient-adaptive, robust-cost, kernel-based, and variable-step strategies—were implemented using the Padasip Python toolbox to cover the spectrum of trade-offs between computational complexity, convergence speed, and robustness to nonstationary noise.

3.2.1 LMS-Family Filters

1. **LMS:**

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu\, e(n)\, \boldsymbol{x}(n) \tag{1}$$

$$e(n) = d(n) - \boldsymbol{w}^{\top}(n)\boldsymbol{x}(n) \tag{2}$$

Here, $\boldsymbol{x}(n)$ is the input vector, $\boldsymbol{w}(n)$ is the filter coefficient vector $d(n)$ the desired signal and $e(n)$ is the a priori error and μ is the step size. LMS offers O(N) complexity per tap update but requires careful choice of $\mu<1/\lambda_{max}$ (largest input-autocorrelation eigenvalue) to ensure stability.

2. **NLMS:**

$$w(n+1) = w(n) + \frac{\mu}{|x(n)|^2 + \epsilon}\, e(n)\, x(n) \tag{3}$$

ϵ is a small regularization constant. By normalizing the step size to the instantaneous input power, NLMS improves convergence stability under varying signal energies.

3. **SSLMS & NSSLMS:**

$$w(n+1) = w(n) + \mu\, \mathrm{sgn}\big(e(n)\big)\, \mathrm{sgn}\big(x(n)\big) \tag{4}$$

$$w(n+1) = w(n) + \frac{\mu}{|x(n)|^2 + \epsilon}\, \mathrm{sgn}\big(e(n)\big)\, \mathrm{sgn}\big(x(n)\big) \tag{5}$$

Sign-quantized updates reduce arithmetic to bit-level operations; NSSLMS adds NLMS-style normalization to the sign-sign rule.

3.2.2 Higher-Order and Robust-Cost Filters

4. **LMF & NLMF:**

$$w(n+1) = w(n) + \mu\, [e(n)]^3\, x(n) \tag{6}$$

$$w(n+1) = w(n) + \frac{\mu}{|x(n)|^2 + \epsilon}\, [e(n)]^3\, x(n) \tag{7}$$

Minimizing fourth-order error, LMF is more resilient to impulsive noise. NLMF extends LMF with input-energy normalization.

5. Llncosh:

$$w(n+1) = w(n) + \mu\ \tanh\big(e(n)\big)\ x(n) \tag{8}$$

The log-hyperbolic cost blends MSE and MAE behaviors, offering robustness across Gaussian and heavy-tailed noise distributions.

3.2.3 Projection- and Recursive-Based Filters

6. AP (Affine Projection):

$$w(n+1) = w(n) + \mu\, X(n)(X^{\top}(n)X(n) + \epsilon I)^{-1}e(n) \tag{9}$$

$$e(n) = d(n) - X^{\top}(n)w(n) \tag{10}$$

here $\boldsymbol{X(n)} = [\boldsymbol{x(n)}, \boldsymbol{x(n-1)}, \dots, \boldsymbol{x(n-P+1)}]$ is $\boldsymbol{M} \times \boldsymbol{P}$ matrix of the last $\boldsymbol{P}$ input vectors, $d(n) = [d(n), d(n-1), \dots, d(n-\boldsymbol{P}+1)]^{\top}$ is the vector of last $\boldsymbol{P}$ desired outputs and $\boldsymbol{e}(n)$ is error vector for the $\boldsymbol{P}$ samples.

Instead of updating the filter using just the most recent input sample (like LMS), the AP algorithm uses the last $\boldsymbol{P}$ input vectors and desired signals. This gives a richer context for adapting the weights, making the algorithm more robust to correlated noise and speech.

7. RLS (Recursive Least Squares):

$$w(n+1) = w(n) + P(n)\, x(n)\, e(n) \tag{11}$$

$$P(n) = \frac{1}{\lambda}\left(P(n-1) - \frac{P(n-1)x(n)x(n)^{\top}\boldsymbol{P}(n-1)}{\lambda + x(n)^{\top}\boldsymbol{P}(n-1)x(n)}\right) \tag{12}$$

λ is the forgetting factor to give more weight to recent data, which is important in nonstationary environments, $\boldsymbol{P}(n)$ is inverse autocorrelation matrix of the input signal for RLS. With $O(N^2)$ complexity, RLS offers the fastest convergence and optimal least-squares tracking at the expense of memory and computation.

3.2.4 Gradient-Adaptive and Kernel-Based Filters

8. GNGD (Generalized Normalized Gradient Descent):

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \boldsymbol{\mu} \cdot \frac{e(n)\,\boldsymbol{x}(n)}{\boldsymbol{\epsilon}(n) + |\boldsymbol{x}(n)|^2} \tag{13}$$

$$\epsilon(n+1) = \epsilon(n) - \rho \cdot \mu \cdot e(n) \cdot e(n-1) \cdot \frac{x^{\top}(n-1)x(n)}{(\epsilon(n) + |x(n-1)|^2)^2} \quad (14)$$

GNGD dynamically learns the regularization term $\epsilon(n)$ that appears in the denominator of the NLMS update. $\epsilon(n)$ is the regularization term at time n. Ρ is the learning rate for the regularization parameter ϵ(n). This allows it to handle signal variations better than NLMS, which uses a fixed ϵ, which makes GNGD maintain stable convergence under rapidly varying noise power.

9. GMCC (Generalized Maximum Correntropy Criterion):

$$w(n+1) = w(n) + \mu\, e(n)\, \exp\left(-\frac{[e(n)]^2}{2\sigma^2}\right) x(n) \quad (15)$$

The exponential term in GMCC uses σ to define the kernel size used to determine correntropy which is a nonlinear similarity measure to emphasize on smaller errors. The correntropy-based term downweights large errors, making GMCC highly robust to outliers and non-Gaussian interference.

3.2.5 Variable Step-Size and Centered Filters

10. VSLMS:

$$\mu_{\mathrm{Ang}}(n) \propto [e(n) - e(n-1)]^2 \quad (16)$$

$$\mu_{\mathrm{Mathews}}(n) \propto \gamma\, \mu(n-1) + (1-\gamma)\, e(n)^2 \quad (17)$$

$$\mu_{\mathrm{Benveniste}}(n) \propto \mu(n-1) + \rho\, e(n)\, \nabla e(n) \quad (18)$$

Three variants dynamically adjust μ based on:

- **Ang's rule** (error-difference squared)
- **Mathews's rule** (exponentially weighted past errors) where γ is initial step size adaptation parameter at the beginning.
- **Benveniste's rule** (gradient-based update) where ρ is learning rate for step size μ, which scales the influence of the instantaneous gradient of the error used for deeper adaptation to the signal's local structure.

11. OCNLMS (Online Centered NLMS):

$$w(n+1) = w(n) + \frac{\mu}{|x(n) - \bar{x}(n)|^2 + \epsilon}\, e(n)\, [x(n) - \bar{x}(n)] \quad (19)$$

This filter uses a centered version of the input vector. $\bar{x}(n)$ is the running mean in OCNLMS. Incorporates a running estimate of input mean into the NLMS update to remove bias and improve tracking in drifting noise conditions.

3.3 Performance Evaluation Metrics

In this research, four objective metrics were employed to evaluate the effectiveness of adaptive filters in speech enhancement tasks. These metrics provide quantitative measures of speech quality, intelligibility, and distortion, which are crucial for assessing the performance of speech enhancement algorithms in practical applications.

3.3.1 Perceptual Evaluation of Speech Quality (PESQ)

PESQ is a widely used standardized metric introduced by ITU-T in recommendation P.862 for assessing speech quality by modeling human auditory perception. It predicts the Mean Opinion Score (MOS) that listeners would assign to a speech sample, allowing for an objective comparison of enhanced and clean speech. Using an auditory model, it compares the clean and enhanced signals to determine speech quality. The PESQ metric is computed as follows:

$$PESQ = a_0 \cdot D_t + a_1 \cdot D_a + a_2 \tag{20}$$

Where D_t and D_a are the disturbance values. For network speech, the regression coefficients a_0, a_1 and a_2 are optimized. The PESQ scores range from -0.5 to 4.5 where better speech is an indication of a high score values.

3.3.2 Log Likelihood Ratio (LLR)

LLR measures the spectral distortion between the enhanced speech and the clean reference by comparing their Linear Prediction Coding (LPC) coefficients, which model the vocal tract envelope. It quantifies how well the LPC model of the enhanced signal matches that of the clean speech, thus indicating preservation of spectral features critical for intelligibility. Since LPC captures vocal tract resonances (formants), LLR is an effective metric for evaluating spectral fidelity post enhancement. Mathematically, the LLR for a frame is defined as:

$$\mathrm{LLR} = \log\left(\frac{a_{clean}^{\top}\mathbf{R}a_{clean}}{a_{enh}^{\top}\mathbf{R}a_{enh}}\right) \tag{21}$$

Where a_{clean} and a_{enh} are the LPC coefficient vectors of clean and enhanced speech respectively. **R** is the autocorrelation matrix of the speech frame. An LLR value close to zero indicates minimal spectral distortion. Higher LLR values indicate greater deviation from the clean spectral envelope, reflecting degradation.

3.3.3 Frequency-Weighted Segmental Signal-to-Noise Ratio (fwSegSNR)

fwSegSNR evaluates the enhancement performance by measuring the signal-to-noise ratio across short speech segments, with additional frequency weighting to emphasize perceptually important bands. Speech intelligibility is not uniform across frequencies; the human ear is more sensitive to certain frequency regions. fwSegSNR accounts for this by weighting the SNR calculation accordingly. The fwSegSNR over ***M*** frames is computed as:

$$\mathrm{fwSegSNR} = \frac{10}{\mathrm{N}} \cdot \sum_{\mathrm{m}=0}^{\mathrm{N}-1} \frac{\sum_{\mathrm{j}=1}^{\mathrm{B}} \mathrm{W}(\mathrm{j},\mathrm{m}) \log_{10}\left(\frac{|\mathrm{Y}(\mathrm{j},\mathrm{m})|^2}{\left(|\mathrm{Y}(\mathrm{j},\mathrm{m})| - |\hat{\mathrm{Y}}(\mathrm{j},\mathrm{m})|\right)^2}\right)}{\sum_{\mathrm{j}=1}^{\mathrm{B}} \mathrm{W}(\mathrm{j},\mathrm{m})} \quad (22)$$

N is the total number of frames, B is the number of bands, and $W(j,m)$ is the weight for the j^{th} frequency band in the m^{th} frame. The clean and enhanced speech spectrums are represented by $|Y(j,m)|$ and $|\hat{Y}(j,m)|$, respectively, A weighting function assigns higher importance to speech-dominant regions. The following is the expression for the weighting function:

$$W(j,m) = Y(j,m)^{\gamma} \quad (23)$$

where γ control the sensitivity of spectral variations. The signal's bandwidth was divided into either 13 or 25 bands, which correspond to the auditory critical bands [19]. We have used 13 bands here. Better speech intelligibility is correlated with higher fwSNRseg values.

3.3.4 Composite speech Quality Measure (C_{OVL})

The composite measure is created as a weighted sum of a number of objective measures for a more reliable estimate of speech quality. It is given as:

$$C_Y = \alpha_0 + \sum_{n=1}^{N} \alpha_n M_n \quad (24)$$

where C_Y is the composite score for a given rating scale, e.g., speech distortion, background noise distortion, or overall quality. The symbols α_n are regression coefficients established by statistical analysis, and M_n are the contributing objective measures. Among the components of the composite measure we look for overall quality (OVL). The use of several objective measures increases the correlation with subjective ratings, thus increasing the robustness of the measurement.

3.4 Process Flowchart

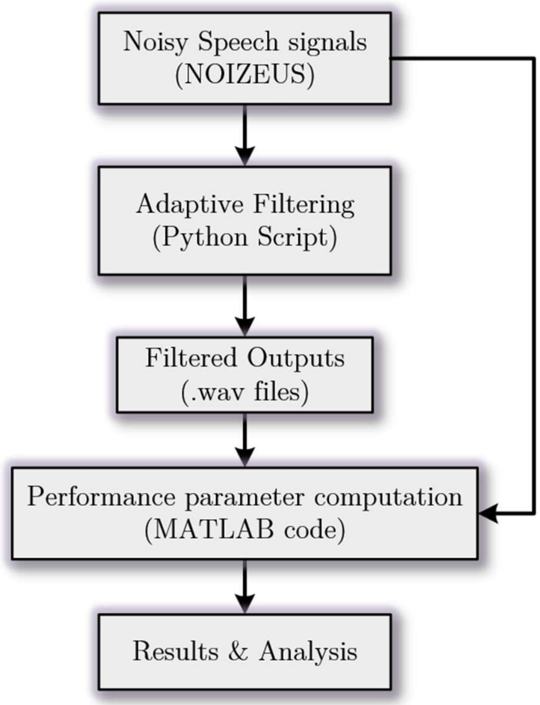

Fig. 1. Process flowchart for adaptive filtering and performance evaluation.

Figure 1 illustrates the adaptive filtering procedure for speech enhancement. The 5dB and 10dB SNR noisy speech samples for eight types of noisy speech samples are taken from the NOIZEUS database. These are fed as input in the python script containing aforementioned fifteen adaptive filters from the Padasip library. After being filtered, the results are saved as.wav files and processed in MATLAB for performance analysis using aforementioned objective speech quality metrics. Finding the optimal filter for each noise environment is the final step, which involves analysing the results.

CHAPTER 4

BENCHMARKING RESULTS AND ANALYSIS

This chapter presents a comprehensive evaluation of fifteen adaptive filters applied to single-channel speech enhancement in realistic acoustic environments. Each filter was tested across multiple noise conditions and signal-to-noise ratios (SNRs), and evaluated using objective metrics such as PESQ, LLR, Segmental SNR, and Composite Score. Results are analyzed to identify the strengths and weaknesses of each algorithm under various noise types.

4.1 Experimental Setup Recap

A brief restatement of key points:

- Dataset: NOIZEUS with 8 real-world noise types.
- SNR Levels: 5 dB and 10 dB.
- Sampling Rate: 8 kHz after IRS filtering.
- Evaluation Metrics: PESQ, LLR, fwSegSNR, Composite Score.
- Test Conditions: 30 utterances × 2 SNRs × 8 noise types per filter.

4.2 Performance Across Noise Types

For each noise type (e.g., car, babble, exhibition), present:

- Quantitative Tables: PESQ, LLR, fwSegSNR, Composite for each filter.
- Bar Charts or Boxplots: Visualizing filter performance variation.
- Commentary: Discuss which filters perform best and why.

4.3 Metric-Wise Filter Comparison

Results were analyzed by using the following metrics:

- PESQ Analysis: Which filters yield the highest perceptual quality.

- LLR Analysis: Performance in preserving spectral envelope.
- fwSegSNR: Signal-level distortion reduction effectiveness.
- Composite Score: Overall robustness across multiple dimensions.

4.4 Benchmarking Results

TABLE 1: Best Performing Filter for Each Noise Type Based on Objective Parameters (For Noisy Speech Samples At 5dB SNR)

Sr. No	Noise Type (5dB samples)	Best Performing Filter based on							
		PESQ		***fwsegSNR$_{OVL}$***		***LLR***		***C$_{OVL}$***	
1	Airport	RLS	4.3028	AP	4.892	$VSLMS_{Math}$	0.3441	RLS	4.6744
2	Babble	RLS	4.2932	AP	4.6989	$VSLMS_{Ben}$	0.3476	RLS	4.6801
3	Car	RLS	4.3847	RLS	4.949	$VSLMS_{Math}$	0.3184	RLS	4.7995
4	Exhibition	RLS	4.2861	RLS, SSLMS	5	GMCC	0.3268	RLS	4.6858
5	Restaurant	RLS	4.3158	AP	4.909	$VSLMS_{Math}$	0.34	RLS	4.7231
6	Station	RLS	4.367	AP	4.9193	$VSLMS_{Ben}$	0.3441	RLS	4.7523
7	Street	RLS	4.333	AP	4.9581	GMCC	0.3232	RLS	4.7326
8	Train	RLS	4.2239	RLS, SSLMS	5	GMCC	0.3135	RLS	4.5977

TABLE 2: Ranking of Adaptive Filters for Each Noise Type Based on Composite Parameter C_{OVL} (For Noisy Speech Samples At 5dB SNR)

Rank	Noise Types (5dB samples)							
	Airport	***Babble***	***Car***	***Exhibition***	***Restaurant***	***Station***	***Street***	***Train***
1	RLS	RLS	RLS	RLS	RLS	RLS	RLS	RLS
2	NLMS	NLMS	NLMS	GMCC	NLMS	NLMS	NLMS	GMCC
3	$VSLMS_{Ang}$	$VSLMS_{Ben}$	$VSLMS_{Math}$	$VSLMS_{Math}$	$VSLMS_{Ang}$	$VSLMS_{Math}$	$VSLMS_{Ben}$	NLMF
4	$VSLMS_{Ben}$	$VSLMS_{Ang}$	$VSLMS_{Ang}$	NLMF	$VSLMS_{Ben}$	$VSLMS_{Ben}$	NLMF	LMF
5	$VSLMS_{Math}$	$VSLMS_{Math}$	$VSLMS_{Ben}$	$VSLMS_{Ang}$	$VSLMS_{Math}$	$VSLMS_{Ang}$	$VSLMS_{Ang}$	OCNLMS
6	Llncosh	GMCC	GMCC	$VSLMS_{Ben}$	Llncosh	GMCC	GMCC	GNGD
7	GMCC	Llncosh	Llncosh	NLMS	GMCC	LMF	$VSLMS_{Math}$	LMS
8	GNGD	NLMF	NLMF	GNGD	GNGD	Llncosh	LMF	$VSLMS_{Ang}$
9	NLMF	LMS	LMS	LMF	OCNLMS	NLMF	Llncosh	Llncosh
10	AP	LMF	OCNLMS	Llncosh	NLMF	AP	OCNLMS	$VSLMS_{Math}$
11	LMS	OCNLMS	LMF	AP	LMF	LMS	GNGD	$VSLMS_{Ben}$
12	OCNLMS	AP	GNGD	OCNLMS	LMS	GNGD	LMS	AP
13	LMF	GNGD	AP	LMS	AP	OCNLMS	AP	NLMS
14	SSLMS	SSLMS	SSLMS	SSLMS	SSLMS	SSLMS	SSLMS	SSLMS
15	NSSLMS	NSSLMS	NSSLMS	NSSLMS	NSSLMS	NSSLMS	NSSLMS	NSSLMS

TABLE 3: Best Performing Filter for Each Noise Type Based on Objective Parameters (For Noisy Speech Samples At 10dB SNR)

Sr. No	**Noise Type (10dB samples)**	**Best Performing Filter based on**							
		PESQ		***fwsegSNR$_{OVL}$***		***LLR***		***C$_{OVL}$***	
1	Airport	RLS	4.2192	AP	4.9992	GMCC	0.3918	RLS	4.5827
2	Babble	RLS	4.2358	RLS	4.4948	GMCC	0.3628	RLS	4.6086
3	Car	RLS	4.3236	AP	4.292	VSLMS$_{Ben}$	0.3407	RLS	4.7193
4	Exhibition	RLS	4.2525	RLS, SSLMS	5	GMCC	0.3389	RLS	4.6396
5	Restaurant	RLS	4.2367	AP	4.8306	VSLMS$_{Mathews}$	0.3878	RLS	4.63
6	Station	RLS	4.2739	AP	4.922	VSLMS$_{Ben}$	0.3773	RLS	4.6436
7	Street	RLS	4.274	AP	4.8486	GMCC	0.3382	RLS	4.66
8	Train	RLS	4.2346	RLS, SSLMS	5	GMCC	0.3493	RLS	4.6005

TABLE 4: Ranking of Adaptive Filters for Each Noise Type Based on Composite Parameter COVL (For Noisy Speech Samples At 10dB SNR)

Rank	**Noise Types (10dB samples)**							
	Airport	***Babble***	***Car***	***Exhibition***	***Restaurant***	***Station***	***Street***	***Train***
1	RLS	RLS	RLS	RLS	RLS	LMS	RLS	RLS
2	NLMS	NLMS	NLMS	NLMS	NLMS	NLMS	NLMS	NLMF
3	VSLMS$_{Ben}$	GMCC	GMCC	GMCC	GMCC	LMF	NLMF	GMCC
4	VSLMS$_{Ang}$	NLMF	VSLMS$_{Ben}$	NLMF	NLMF	NLMF	GMCC	LMF
5	LMF	VSLMS$_{Math}$	NLMF	VSLMS$_{Math}$	VSLMS$_{Math}$	SSLMS	VSLMS$_{Ang}$	GNGD
6	VSLMS$_{Math}$	VSLMS$_{Ang}$	LMF	VSLMS$_{Ang}$	LMF	NSSLMS	LMF	OCNLMS
7	GMCC	LMF	VSLMS$_{Math}$	VSLMS$_{Ben}$	VSLMS$_{Ang}$	RLS	VSLMS$_{Math}$	VSLMS$_{Ang}$
8	AP	AP	VSLMS$_{Ang}$	LMF	AP	GNGD	VSLMS$_{Ben}$	VSLMS$_{Ben}$
9	OCNLMS	VSLMS$_{Ben}$	Llncosh	OCNLMS	VSLMS$_{Ben}$	AP	AP	VSLMS$_{Math}$
10	NLMF	GNGD	GNGD	GNGD	GNGD	GMCC	GNGD	Llncosh
11	Llncosh	OCNLMS	AP	AP	Llncosh	OCNLMS	Llncosh	LMS
12	LMS	Llncosh	OCNLMS	Llncosh	OCNLMS	Llncosh	OCNLMS	AP
13	GNGD	LMS	LMS	LMS	LMS	VSLMS$_{Ang}$	LMS	NLMS
14	SSLMS	SSLMS	SSLMS	SSLMS	SSLMS	VSLMS$_{Ben}$	SSLMS	SSLMS
15	NSSLMS	NSSLMS	NSSLMS	NSSLMS	NSSLMS	VSLMS$_{Math}$	NSSLMS	NSSLMS

The noisy speech samples were processed through adaptive filters. The data consisted of eight types of noise, at two SNR levels (5 dB and 10 dB) with 30 speech samples for each case. This provided:

$$8(noise\ types) \times 2(SNR\ levels) \times 30(speech\ samples) = 480\ input\ samples$$

resulting in 480 input samples in total. These input samples were then processed using 15 adaptive filters, resulting in:

$$480\ input\ samples \times 15\ adaptive\ filters = 7{,}200\ filtered\ outputs$$

Each filtered output is a unique combination of speech sample, noise type, SNR level, and adaptive filter. For measuring performance, the objective measure scores for the 30 speech samples for each noise-filter combination were averaged. Appendix 1 & 2 respectively contains the averaged results for 5 dB & 10 dB samples respectively. The tables in this section are the top findings among the results mentioned in Appendix 1. These were separately computed for the 5 dB and 10 dB SNR levels, and the filter with the highest performance was determined for each of the noise types.

For PESQ and LLR, the raw computed absolute value was taken, whereas fwSNRseg was computed using 25 critical bands based on the Bark psychoacoustic scale [19], with score mapped to a 0-5 MOS like scale, similar to the composite measure, which was also mapped on a 0-5 scale. The MATLAB codes used to compute these measures were adapted and modified from [18] for compatibility with the current MATLAB version. Table 1 and Table 3 highlights the top-performing filters for each noise type based on these objective measures for 5 dB and 10 dB respectively. Similarly, Table 2 and 4 represents the filter ranking across each noise type, based on the composite measure C_{OVL} as it showed the highest correlation with subjective listening scores for each SNR levels. Both of these SNR levels represent noisier to less noisy acoustic situations.

CHAPTER 5

ENSEMBLE-BASED ADAPTIVE FILTERING SYSTEM DESIGN

5.1 Motivation & Background

Noisy speech improvement is important in order to improve communication quality in various applications like mobile communication, car voice assistants, and hearing aids. Automotive environments involve much engine, tire, and other noise background which badly deteriorates the quality and intelligibility of the speech signals. The challenge to real-time systems is that this should be efficiently carried out without introducing substantial latency or distortion.

Conventional adaptive filters such as Recursive Least Squares (RLS) (Venkateswarlu et al., 2021) and Normalized Least Mean Squares (NLMS) (Diniz, 2020) have been traditionally used for filtering out noise. The filters themselves, however, cannot be run in a stable manner in dynamic noise environments, particularly for car-type environments where the noise environment of interest tends to keep changing. RLS filter's need for heavy computations also renders it inappropriate for low power-embedded systems, which provokes the design of energy-efficient alternatives.

Individual adaptive filters do not adapt best to varying noise profiles and, as such, provide poor speech enhancement quality. Although RLS is more precise, its computational complexity renders it impossible for low power real-time processing, especially when applied in resource-constrained environments. An ensemble-based approach that utilizes a bank of adaptive filters can provide enhanced robustness by controlling dynamically filter contributions based on their individual error performance.

In car environments, speech enhancement proves challenging owing to non-stationary noise from sources such as traffic, wind, and engines. Previous approaches utilized multi-channel adaptive Wiener filtering for high-frequency sub-bands (Chen et al., 2012) and spectral subtraction for low-frequency sub-bands to combat noise and distortion (Visser et al., 2001). In speech presence estimation, sub-band-based methods later surpassed more traditional methods such as Wiener and MMSE-based estimators (Fingscheidt et al., 2008). To compensate speech enhancement for various conditions, environment-adaptive techniques brought in sub-band processing and statistical modeling. A robust system enhanced speech recognition with time- and frequency-domain beamformers without retraining in diverse environments (Ramesh Babu & Sridhar, 2020).

Later, dynamic multi-microphone systems with power ratio-based controls were developed to control multiple talkers and ambient noise (Matheja et al., 2013). With pipelined architectures, real-time capability was delivered by psychoacoustic models and perceptual filter banks (Yang et al., 2008). Real-time adaptive Wiener filters and blind source separation (BSS) techniques further augmented noise cancellation in automotive environments (Djendi, 2016).

Recent developments utilized adaptive parallel filter methods to dynamically suppress road noise and beamforming combined with Kalman filtering for enhanced intelligibility (Yin et al., 2023). Time difference of arrival (TDOA) and source separation with microphone arrays (Pathrose & Govindaraj, 2024) were examined in recent studies for adaptive signal adjustment. Norm-based adaptive filters provided robust solutions for channel estimation and in-car echo cancellation (Huang et al., 2022). Yet, existing methods often lack in dynamically responding to changing noise patterns and have difficulty in balancing computational complexity and noise reduction. Whereas methods such as spectral subtraction and Wiener filtering fail in non-stationary environments, methods such as RLS are effective but computationally expensive.

This part of the research aims to develop an ensemble-based adaptive filtering system for speech enhancement in car noise environments. A performance-based dynamic weighting scheme will adaptively regulate the contribution of multiple adaptive filters, ensuring improved noise attenuation with low computational complexity, making it ideal for real-time applications in challenging automotive environments.

5.2 Methodology

5.2.1 Model Diagram

Figure 1 shows the proposed ensemble adaptive filter system, that pre-emphasizes a noisy speech signal after noise estimate subtraction. Three parallel adaptive filters-NLMS [2], GMCC [13], and VSLMS (Mathew's) [14] process the pre-emphasized signal. The enhanced speech signal is produced by dynamically combining the filter outputs and de-emphasizing the resultant signal.

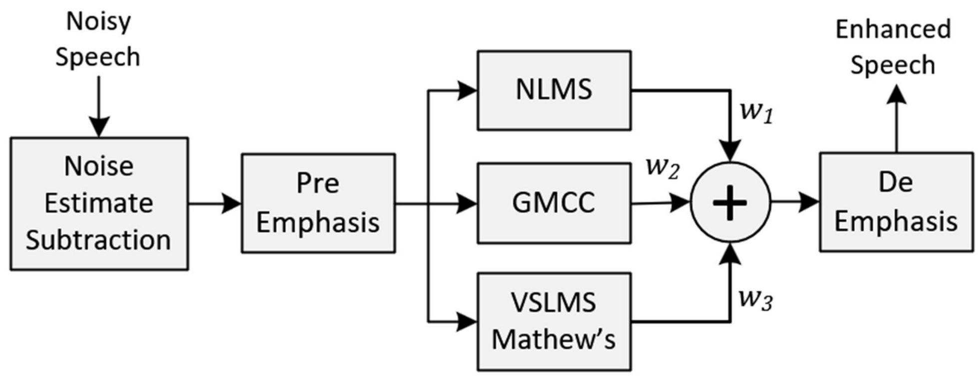

Fig. 2. Block diagram of the proposed ensemble-based adaptive filtering system model for speech enhancement in car noise environment

5.2.2 Pre-Processing

The noisy speech signal is conditioned during the pre-processing phase by noise estimate subtraction and pre-emphasis. The pre-computed noise profile is obtained by averaging the differences between 30 noisy and their corresponding 30 clean speech samples available in the dataset. In the frequency domain, the estimate noise spectrum is subtracted from signals spectrum, and the signal is converted back by IFFT. The pre-emphasis is the following step, where high-frequency components are boosted to preserve the speech details. All of these processes assure that input is optimized to provide efficient speech enhancement and attenuation of noise is supplied to the filters.

5.2.3 Parallel Filtering

Here we are applying three adaptive filters in parallel: NLMS, GMCC, and VSLMS (Mathew's). In our preliminary analysis, it was found that these filters showed exceptional individual performance in Car noise conditions. These were sourced from python Padasip library [15]. Each filter iteratively updates its weights using a different adaptation rule. NLMS uses normalized step-size control to improve stability and convergence speed. GMCC employs a kernel-based method to enhance error minimization by accounting for higher-order dependencies. VSLMS (Mathew's) dynamically adjusts the step-size according to the error magnitude, allowing for better trade-offs between convergence speed and steady-state error.

5.2.4 Dynamic weight assignment & post-processing

To enhance speech robustness, an error-based dynamic weight assignment strategy combines outputs from three parallel adaptive filters. Each filter's error—defined as the difference between the desired clean signal and its output—guides weight adjustments. Filters with smaller errors are given higher weights, while less accurate ones contribute less. A normalized inverse error measure continuously updates these weights, ensuring the most effective filter dominates the final signal. Once combined, the output undergoes post-processing: de-emphasis reverses the high-frequency boost applied earlier to restore spectral balance, and normalization adjusts the amplitude to maintain clarity and prevent distortion.

5.3 Experimental Setup

5.3.1 Dataset

We use the NOIZEUS Speech Corpus, the same dataset described earlier in Section 3.1.

5.3.2 Performance parameters

The ensemble filter's performance was assessed using the objective speech quality metrics mentioned in Section 3.3.

CHAPTER 6

ENSEMBLE FILTER RESULTS AND EVALUATION

The Composite Objective Measure (C_{OVL}), which closely correlates with subjective human perception of speech quality, was used as a principal metric in evaluating the performance of each adaptive filter. Figure 2 displays the C_{OVL} scores for all 30 speech samples under both 5 dB and 10 dB SNR conditions. The results clearly indicate the consistent superiority of the Ensemble-based adaptive filtering approach.

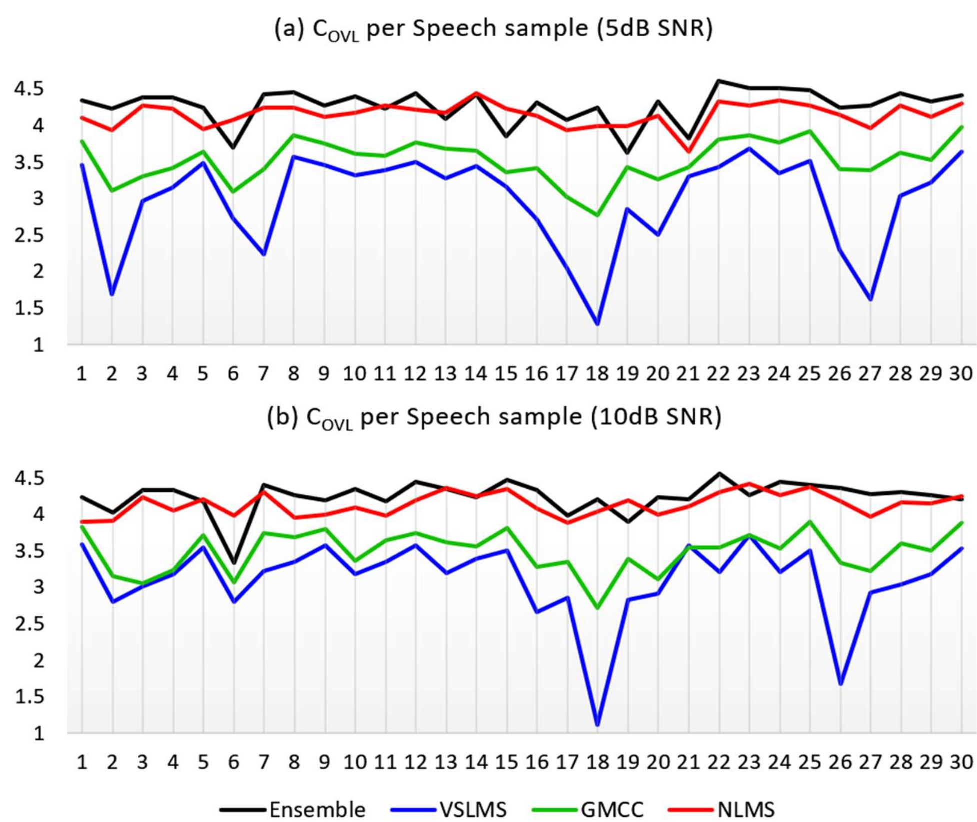

Fig. 3. C_{OVL} values per speech sample for each filter tested at (a) 5dB & (b) 10dB SNR

Under the 5 dB SNR condition, the Ensemble filter outperformed all individual filters in 25 out of 30 samples, while in the remaining 5 samples, the NLMS filter marginally surpassed it. Similarly, under the 10 dB SNR condition, the Ensemble filter achieved the highest C_{OVL} in 26 out of 30 samples, further reinforcing its reliability across varying noise levels.

The average C_{OVL} scores summarized in Table 1 reinforce these per-sample observations. The Ensemble filter achieved the highest mean COVL values among all filters tested, under both noise conditions. This consistent advantage highlights the Ensemble's ability to effectively model speech quality improvements across different noise scenarios. Its dynamic weighting strategy—combining the strengths of multiple adaptive filters—results in more perceptually pleasing and intelligible speech reconstructions.

TABLE 5. Average values of performance parameters for each filter tested at 5dB speech samples

S. No.	Filter	Performance Parameters *for Speech samples at 5dB SNR*			
		PESQ	***LLR***	***fwsegSNR***	C_{OVL}
1	NLMS	3.75	0.77	1.27	4.15
2	$VSLMS_{Mathews}$	2.43	0.91	1.91	2.98
3	GMCC	3.14	0.97	1.74	3.52
4	Ensemble	3.58	0.28	2.13	4.27

TABLE 6. Average values of performance parameters for each filter tested at 10dB SNR speech samples

S. No.	Filter	Performance Parameters *for Speech samples at 10dB SNR*			
		PESQ	***LLR***	***fwsegSNR***	C_{OVL}
1	NLMS	3.76	0.82	1.36	4.14
2	$VSLMS_{Mathews}$	2.65	0.99	1.79	3.11
3	GMCC	3.15	1.04	1.97	3.49
4	Ensemble	3.60	0.36	1.81	4.24

These findings affirm that the Ensemble filter not only performs well in most individual cases but also demonstrates the best overall speech enhancement performance when averaged across all samples and SNR conditions. This makes it a strong candidate for real-world deployment, particularly in challenging acoustic environments such as automotive or public spaces.

CHAPTER 7

CONCLUSIONS AND FUTURE WORK

This thesis presented a comprehensive benchmarking study of adaptive filtering techniques for speech enhancement in realistic acoustic environments, with a primary focus on automotive noise conditions. A total of fifteen adaptive filters from the Padasip library—including LMS, NLMS, RLS, GMCC, VSLMS variants, and others—were evaluated using objective speech quality and intelligibility metrics. The evaluation was conducted on a phonetically balanced dataset with eight real-world noise types at 5 dB and 10 dB SNR levels.

Among the individual filters, GMCC and VSLMS (Mathew's variant) consistently demonstrated strong performance in high-noise environments. However, variability across noise types revealed limitations in generalizability for standalone filters. To address this, an Ensemble-based adaptive filtering approach was proposed, combining the outputs of selected filters using a dynamic weighting strategy.

The results clearly showed that the Ensemble filter achieved superior performance across all objective metrics, particularly the Composite Objective Measure (C_{OVL}), which closely correlates with perceptual quality. In over 80% of the speech samples, the Ensemble filter produced the highest C_{OVL} scores, and its average scores across all conditions were the highest among all tested filters. These findings demonstrate the robustness and adaptability of the Ensemble framework, especially in fluctuating real-world noise conditions such as car, exhibition, and restaurant environments.

Future Work

While the current work provides a solid benchmarking framework and a strong Ensemble-based solution, several promising directions remain open for future research:

- Psychoacoustic Model Integration: Incorporating human auditory models can help prioritize perceptually important features in the speech signal, potentially improving both intelligibility and quality.
- Fuzzy Logic-Based Weighting: Replacing or enhancing the dynamic weighting strategy in the Ensemble with fuzzy logic can enable context-aware filter selection, further boosting robustness.

- Deep Learning Hybridization: Exploring the integration of adaptive filters with deep neural networks (e.g., LSTM, CNN, or transformer-based denoisers) may lead to hybrid systems that leverage both signal processing and data-driven learning.
- Real-Time Implementation: Implementing the proposed Ensemble model in embedded systems or low-power digital signal processors (DSPs) can enable practical applications in hearing aids, in-car voice assistants, and mobile devices.
- Subjective Evaluation: Although objective metrics provide reliable estimates, future work should include large-scale Mean Opinion Score (MOS) studies to validate perceptual benefits in real-world scenarios.
- Extension to Multichannel and Binaural Inputs: Leveraging spatial information from stereo or multichannel recordings can significantly improve enhancement performance in complex acoustic scenes.

In summary, this thesis lays a strong foundation for adaptive filter benchmarking and offers a promising Ensemble-based speech enhancement solution, with multiple pathways open for expanding its applicability and performance.

REFERENCES

1. P. S. R. Diniz, Adaptive Filtering: Algorithms and Practical Implementation. Cham: Springer International Publishing, 2020, doi: 10.1007/978-3-030-29057-3.
2. M. Kalamani and M. Krishnamoorthi, “Modified least mean square adaptive filter for speech enhancement,” in Applied Speech Processing, Elsevier, 2021, pp. 47–73.
3. E. Walach and B. Widrow, “The least mean fourth (LMF) adaptive algorithm and its family,” IEEE Trans. Inform. Theory, vol. 30, no. 2, pp. 275–283, Mar. 1984, doi: 10.1109/TIT.1984.1056886.
4. A. Zerguine, “Convergence and steady-state analysis of the normalized least mean fourth algorithm,” Digital Signal Processing, vol. 17, no. 1, pp. 17–31, Jan. 2007, doi: 10.1016/j.dsp.2006.01.005.
5. M. Z. U. Rahman, R. A. Shaik, and D. V. R. K. Reddy, “Noise cancellation in ECG signals using normalized Sign-Sign LMS algorithm,” in 2009 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT), Ajman, UAE: IEEE, Dec. 2009, pp. 288–292, doi: 10.1109/ISSPIT.2009.5407510.
6. S. C. Venkateswarlu, N. U. Kumar, and A. Karthik, “Speech enhancement using recursive least square based on real-time adaptive filtering algorithm,” in 2021 6th International Conference for Convergence in Technology (I2CT), Maharashtra, India: IEEE, Apr. 2021, pp. 1–4, doi: 10.1109/I2CT51068.2021.9417929.
7. M. Alam, Md. I. Islam, and M. R. Amin, “Performance Comparison of STFT, WT, LMS and RLS Adaptive Algorithms in Denoising of Speech Signal,” IJET, vol. 3, no. 3, pp. 235–238, 2011, doi: 10.7763/IJET.2011.V3.230.
8. R. Ram and M. N. Mohanty, “Performance Analysis of Adaptive Algorithms for Speech Enhancement Applications,” Indian Journal of Science and Technology, vol. 9, no. 44, Nov. 2016, doi: 10.17485/ijst/2016/v9i44/102867.
9. K. Ozeki, Theory of Affine Projection Algorithms for Adaptive Filtering, vol. 22, Mathematics for Industry. Tokyo: Springer Japan, 2016, doi: 10.1007/978-4-431-55738-8.
10. D. P. Mandic, “A Generalized Normalized Gradient Descent Algorithm,” IEEE Signal Process. Lett., vol. 11, no. 2, pp. 115–118, Feb. 2004, doi: 10.1109/LSP.2003.821649.
11. C. Liu and M. Jiang, “Robust adaptive filter with lncosh cost,” Signal Processing, vol. 168, p. 107348, Mar. 2020, doi: 10.1016/j.sigpro.2019.107348.
12. B. Chen, L. Xing, H. Zhao, N. Zheng, and J. C. Principe, “Generalized Correntropy for Robust Adaptive Filtering,” IEEE Trans. Signal Process., vol. 64, no. 13, pp. 3376–3387, Jul. 2016, doi: 10.1109/TSP.2016.2539127.
13. W. P. Ang and B. Farhang-Boroujeny, “A new class of gradient adaptive step-size LMS algorithms,” IEEE Trans. Signal Process., vol. 49, no. 4, pp. 805–810, Apr. 2001, doi: 10.1109/78.912925.

14. V. J. Mathews and Z. Xie, "A stochastic gradient adaptive filter with gradient adaptive step size," IEEE Trans. Signal Process., vol. 41, no. 6, pp. 2075–2087, Jun. 1993, doi: 10.1109/78.218137.
15. M. Cejnek and J. Vrba, "Online centered NLMS algorithm for concept drift compensation," Neural Network World, vol. 31, no. 5, pp. 329–341, 2021, doi: 10.14311/NNW.2021.31.018.
16. M. Cejnek and J. Vrba, "Padasip: An open-source Python toolbox for adaptive filtering," Journal of Computational Science, vol. 65, p. 101887, Nov. 2022, doi: 10.1016/j.jocs.2022.101887.
17. Y. Hu and P. C. Loizou, "Subjective comparison and evaluation of speech enhancement algorithms," Speech Communication, vol. 49, no. 7–8, pp. 588–601, Jul. 2007, doi: 10.1016/j.specom.2006.12.006.
18. Y. Hu and P. C. Loizou, "Evaluation of objective quality measures for speech enhancement," IEEE Trans. Audio Speech Lang. Process., vol. 16, no. 1, pp. 229–238, Jan. 2008, doi: 10.1109/TASL.2007.911054.
19. P. C. Loizou, Speech Enhancement: Theory and Practice. CRC Press, 2007.
20. Y. H. Chen, S. J. Ruan, and T. Qi, "An automotive application of real-time adaptive Wiener filter for non-stationary noise cancellation in a car environment," in 2012 IEEE Int. Conf. on Signal Processing, Communication and Computing (ICSPCC), Aug. 2012, pp. 597–601.
21. E. Visser, T. Lee, and M. Otsuka, "Speech enhancement in a noisy car environment," in Proc. 3rd Int. Conf. on Independent Component Analysis and Source Separation, Dec. 2001, pp. 272–277.
22. T. Fingscheidt, S. Suhadi, and S. Stan, "Environment-optimized speech enhancement," IEEE Trans. Audio, Speech, and Language Processing, vol. 16, no. 4, pp. 825–834, Apr. 2008.
23. G. R. Babu and G. V. Sridhar, "Speech enhancement using beamforming and Kalman Filter for In-Car noisy environment," in Microelectronics, Electromagnetics and Telecommunications: Proc. of the Fifth ICMEET 2019, Springer, 2020, pp. 549–557.
24. T. Matheja, M. Buck, and T. Fingscheidt, "A dynamic multi-channel speech enhancement system for distributed microphones in a car environment," EURASIP J. Adv. Signal Process., vol. 2013, no. 1, pp. 1–21, 2013.
25. C. H. Yang, J. C. Wang, J. F. Wang, C. H. Wu, and K. H. Chang, "Design and implementation of subspace-based speech enhancement under in-car noisy environments," IEEE Trans. Vehicular Technology, vol. 57, no. 3, pp. 1466–1479, May 2008.
26. M. Djendi, "An efficient frequency-domain adaptive forward BSS algorithm for acoustic noise reduction and speech quality enhancement," Computers & Electrical Engineering, vol. 52, pp. 12–27, May 2016.
27. L. Yin et al., "Adaptive parallel filter method for active cancellation of road noise inside vehicles," Mechanical Systems and Signal Processing, vol. 193, p. 110274, Jun. 2023.
28. J. Pathrose and V. Govindaraj, "In-Car Speech Enhancement Based on Source Separation Technique," Audiology and Speech Research, vol. 20, no. 3, pp. 172–182, Jul. 2024.

29. X. Huang, Y. Li, X. Han, and H. Tu, "Lawson-norm-based adaptive filter for channel estimation and in-car echo cancellation," IEEE Trans. Circuits Syst. II: Express Briefs, vol. 69, no. 4, pp. 2376–2380, Jan. 2022.

APPENDIX

Appendix 1: Each row is the average result of 30 speech samples (5dB)

Matlab functions		PESQ		LLR	comp_fwseg_mars			composite				
Filter	**Noise Type**	**PESQ Score**	**MOS Score**	**LLR**	**SIG**	**BAK**	**OVL**	**segSNR**	**wss_dist**	**Csig**	**Cbak**	**Covl**
airport	LMS	3.741728079	3.840001308	0.5489552	3.107587	1.970173	2.537244	-5.99291	17.33926	4.626248	2.923618	4.203651
	NLMS	4.005705371	4.149840381	0.3728405	3.365387	2.281203	2.621412	-4.42538	13.81596	4.91858	3.173217	4.530987
	LMF	3.773290414	3.885002106	0.5970712	2.645147	2.393034	2.130847	-8.54011	23.97809	4.536799	2.731759	4.157952
	NLMF	3.902050691	4.022451512	0.5492016	2.509869	1.929533	2.256624	-8.37648	22.48027	4.668857	2.8141	4.296598
	SSLMS	3.406018317	3.41406788	0.5219442	3.455916	1.243486	2.160939	-4.4362	17.08284	4.456003	2.863016	3.949029
	NSSLMS	2.327844524	2.030181887	1.4522046	1.619277	1.184023	1.389962	-9.66617	42.62846	2.618716	1.843235	2.437538
	RLS	4.167549185	4.302848603	0.4682001	4.39431	1	3.388391	-2.98562	4.961962	4.995677	3.403261	4.674425
	GNGD	3.863784448	3.991860349	0.5387583	2.941492	2.183479	2.595633	-7.26866	18.47761	4.691219	2.89362	4.299159
	AP	3.744952507	3.869121911	0.4374875	4.942951	4.003256	4.892048	-1.35374	14.87975	4.767114	3.234644	4.280535
	GMCC	3.88714737	4.016846493	0.4410605	2.582428	1.860895	2.889506	-9.82035	25.47149	4.727231	2.695074	4.31903
	OCNLMS	3.787084385	3.901245822	0.5845367	2.689704	2.014987	2.564896	-7.1189	20.24544	4.591678	2.854017	4.201602
	Llncosh	3.85846757	3.98894972	0.4535715	3.268636	1.897305	3.040277	-4.61627	15.50304	4.790862	3.079001	4.359317
	VSLMS_Ang	3.87769668	4.012004585	0.3619358	3.59621	1.816525	3.243873	-3.3759	10.74285	4.89711	3.199657	4.455035
	VSLMS_Ben	3.866870186	4.0005613	0.3621558	4.100515	1.345206	3.47582	-3.3021	10.1179	4.906907	3.203506	4.450581
	VSLMS_Mathews	3.84126384	3.97599212	0.3441205	3.333235	1.913833	3.447156	-3.44638	10.39055	4.920312	3.180269	4.437294
babble	LMS	3.844855078	3.965859096	0.5204961	2.817386	2.139115	2.943683	-5.94243	17.35133	4.718126	2.976008	4.301155
	NLMS	3.985778957	4.134131677	0.405742	2.980914	1.939662	2.544223	-4.31528	12.31245	4.928276	3.181153	4.508625
	LMF	3.879442797	3.995074734	0.5342889	2.610341	2.320903	2.765369	-8.38963	21.84243	4.663853	2.80693	4.290499
	NLMF	3.904570631	4.01443251	0.5588909	2.244597	1.832212	2.587147	-8.60439	21.11977	4.668029	2.81047	4.303189
	SSLMS	3.455892539	3.488142444	0.4841023	2.97367	1.894523	2.982159	-4.36762	17.28181	4.523226	2.889784	4.00716
	NSSLMS	2.368781773	2.011099181	1.3007351	1.562654	2.279749	1.081036	-9.63016	44.39076	2.783402	1.848842	2.524158
	RLS	4.154430488	4.293202689	0.4359412	3.861436	1	4.612342	-2.93622	4.991062	4.995004	3.399898	4.680177
	GNGD	3.831622451	3.956114174	0.5693252	2.332928	2.353613	2.135752	-7.35519	19.52831	4.638747	2.865441	4.250263
	AP	3.729102019	3.848568426	0.4589935	4.944736	3.646591	4.698918	-1.54067	15.19993	4.732545	3.213049	4.254523
	GMCC	3.848738893	3.971481978	0.3892741	3.065803	2.436669	2.751338	-9.85242	22.79932	4.765812	2.6934	4.333331
	OCNLMS	3.835909814	3.950726646	0.550224	2.49964	2.28061	2.19166	-7.33416	20.46665	4.651316	2.862246	4.256926
	Llncosh	3.800002454	3.925613941	0.4541278	3.41104	1.75195	3.185733	-4.76714	16.05889	4.769907	3.037659	4.308076
	VSLMS_Ang	3.841798534	3.969540719	0.3712233	3.772317	1.504487	3.598614	-3.41997	10.75583	4.883563	3.179631	4.421291
	VSLMS_Ben	3.876587614	4.011622964	0.3476906	3.866376	1.463337	3.141107	-3.33675	10.65824	4.90714	3.202186	4.462028
	VSLMS_Mathews	3.82415444	3.952263608	0.3625761	3.169598	1.649021	3.473235	-3.3793	10.87858	4.884735	3.1729	4.410655

Matlab functions		PESQ		LLR	comp_fwseg_mars			composite				
Filter	**Noise Type**	**PESQ Score**	**MOS Score**	**LLR**	**SIG**	**BAK**	**OVL**	**segSNR**	**wss_dist**	**Csig**	**Cbak**	**Covl**
car	LMS	3.800352023	3.901184402	0.4336302	2.932637	2.167119	3.003792	-6.49019	17.9092	4.772305	2.916322	4.3059
	NLMS	3.931568296	4.073411087	0.3712907	2.250418	2.565789	2.637479	-4.20902	12.27543	4.927477	3.162193	4.482884
	LMF	3.836248076	3.941462273	0.5130721	3.071462	2.436538	2.43523	-9.31454	22.64272	4.64715	2.722412	4.260988
	NLMF	3.951525572	4.090674664	0.5187467	2.723098	1.578881	2.464946	-8.90462	22.65526	4.730091	2.803251	4.350793
	SSLMS	3.554150563	3.619267759	0.4305961	3.797759	2.130407	4.443581	-4.40614	16.12538	4.647941	2.94242	4.121748
	NSSLMS	2.606069825	2.310655791	0.9406086	2.476076	1.449175	1.611894	-9.40609	36.74277	3.365889	2.029918	2.953095
	RLS	4.263447283	4.38476589	0.3765787	4.217693	1.702046	4.949099	-3.04179	4.822485	5	3.446538	4.799509
	GNGD	3.790304538	3.949184802	0.5341556	2.747615	1.993884	2.43233	-7.80345	20.60046	4.641704	2.809945	4.227504
	AP	3.700305216	3.810260441	0.5566625	4.531959	4.585579	4.867955	-1.18156	15.30393	4.613743	3.22118	4.180607
	GMCC	3.966827117	4.107887555	0.3509943	2.381006	2.329876	2.572013	-9.95491	23.43046	4.873435	2.738971	4.443574
	OCNLMS	3.891761937	4.025454879	0.5563384	2.381018	2.322515	2.405635	-8.14386	20.98641	4.66734	2.834294	4.295118
	Llncosh	3.840070178	3.969677599	0.4111523	2.767775	2.674725	2.793443	-5.02439	14.91146	4.808466	3.048637	4.370366
	VSLMS_Ang	3.893312014	4.031298125	0.3702065	3.028412	1.985399	4.00431	-3.59293	10.43341	4.905663	3.195615	4.465537
	VSLMS_Ben	3.855622654	3.990579882	0.3427564	3.380318	2.236585	3.900045	-3.40559	10.04368	4.918246	3.192129	4.451979
	VSLMS_Mathews	3.872047428	4.008544115	0.3184392	3.06523	2.038683	3.912174	-3.41062	9.524012	4.926099	3.203302	4.481289
exhibition	LMS	3.698485194	3.797707585	0.4886195	2.96872	2.4885	2.668544	-6.86007	20.29059	4.637782	2.827657	4.179073
	NLMS	3.855107571	3.98105975	0.4642319	4.090449	1.859343	3.500488	-3.73468	13.07508	4.801111	3.149931	4.368149
	LMF	3.900822402	4.03205901	0.5251243	2.369055	2.318446	2.31648	-9.33717	22.42473	4.697322	2.753378	4.308325
	NLMF	4.0030036	4.145504076	0.4594395	2.581362	1.962547	2.719888	-9.27909	22.12703	4.79958	2.807964	4.426296
	SSLMS	3.429357159	3.450185616	0.4734335	4.954974	4.603035	5	-4.30715	20.08849	4.492943	2.861263	3.971615
	NSSLMS	2.353456625	2.073030819	0.8679744	4.007606	4.120541	4.564569	-9.40292	46.09273	3.204154	1.845673	2.721481
	RLS	4.142225169	4.286175596	0.3944009	5	2.205097	5	-2.98247	5.820762	5	3.385343	4.685813
	GNGD	3.872112852	3.992613015	0.4823601	3.010712	2.704108	3.051514	-8.07156	21.78503	4.731884	2.823866	4.311587
	AP	3.734145464	3.856107032	0.535839	4.96981	4.733333	4.625187	-1.16686	16.38846	4.645815	3.23069	4.210918
	GMCC	3.997943259	4.142191562	0.3268565	2.253904	2.14533	3.051866	-9.94661	20.93759	4.908663	2.771818	4.498431
	OCNLMS	3.76171044	3.870119124	0.487021	2.664991	1.986589	2.179298	-8.25072	24.41877	4.637923	2.741371	4.201891
	Llncosh	3.702168613	3.803484365	0.4362518	4.042779	1.682782	3.343539	-4.88397	16.20179	4.719143	2.982534	4.237472
	VSLMS_Ang	3.84854206	3.982369049	0.3792734	4.309685	2.171843	4.345397	-3.27704	11.38994	4.882206	3.18742	4.418159
	VSLMS_Ben	3.84252827	3.97355329	0.4100445	4.413	1.782343	4.439832	-3.41987	11.83749	4.869541	3.172414	4.39443
	VSLMS_Mathews	3.885920769	4.027183266	0.3871821	4.497948	2.68527	4.87083	-3.27084	11.68128	4.902455	3.203638	4.44216

Matlab functions		PESQ		LLR	comp_fwseg_mars			composite				
Filter	Noise Type	PESQ Score	MOS Score	LLR	SIG	BAK	OVL	segSNR	wss_dist	Csig	Cbak	Covl
restaurant	LMS	3.788675987	3.903567749	0.5556141	2.504534	2.375395	2.700609	-5.96241	17.76401	4.645786	2.945007	4.235062
	NLMS	3.970496277	4.113344067	0.4010422	2.758131	2.155646	2.592605	-4.44104	12.75572	4.906799	3.162821	4.495626
	LMF	3.916619231	4.047502912	0.5608115	2.970547	1.722469	2.407304	-8.56293	25.41189	4.639075	2.788796	4.28186
	NLMF	3.909681269	4.038734627	0.5334156	2.536462	2.493467	2.17503	-8.41217	23.86656	4.679189	2.805795	4.301119
	SSLMS	3.406654417	3.415699763	0.4476047	3.715177	4.008204	4.123974	-4.24836	18.31424	4.521799	2.866534	3.978983
	NSSLMS	2.328595498	1.996718289	1.3575361	1.784736	2.098313	3.216713	-9.72233	46.71613	2.679793	1.807549	2.446448
	RLS	4.180658003	4.315877502	0.3956281	4.737708	1.10957	4.408682	-2.81664	4.820341	5	3.421164	4.723126
	GNGD	3.891906031	4.02695631	0.5374904	2.43407	1.98199	2.21442	-7.20203	20.27101	4.684895	2.898706	4.309892
	AP	3.710356994	3.826858168	0.4767015	5	3.981317	4.909029	-1.3489	16.0456	4.695409	3.210251	4.224447
	GMCC	3.864024395	3.979824736	0.413197	2.769276	2.197277	2.326169	-9.76635	23.20562	4.763252	2.703285	4.330543
	OCNLMS	3.856913061	3.97909258	0.4932464	2.27576	2.263844	2.314038	-7.23592	19.94868	4.727563	2.882101	4.306632
	Llncosh	3.84171207	3.968848646	0.4392568	2.932501	2.153457	2.644442	-4.70684	14.4844	4.825272	3.072416	4.360288
	VSLMS_Ang	3.824173813	3.954340269	0.3453205	3.182581	1.726133	3.371068	-3.41402	11.0116	4.89799	3.169791	4.418575
	VSLMS_Ben	3.822766572	3.947275496	0.3445837	3.750131	1.30487	2.8656	-3.41118	10.91524	4.890093	3.169971	4.418494
	VSLMS_Mathews	3.812431321	3.937857034	0.3400168	3.766425	1.706206	3.430797	-3.34912	10.64647	4.891508	3.170822	4.414393
station	LMS	3.823562523	3.950748288	0.5308145	2.6269	2.310522	2.493504	-6.306	17.8862	4.682012	2.939182	4.274987
	NLMS	3.98935757	4.133495299	0.4058286	3.059984	2.026316	2.564327	-4.41929	11.97714	4.93429	3.178658	4.513809
	LMF	3.923406638	4.064248451	0.4814857	2.297949	1.843534	2.022855	-9.07524	23.48455	4.741861	2.773257	4.34143
	NLMF	3.914266159	4.054172304	0.5255748	2.354746	2.451259	2.172774	-8.84123	23.77854	4.690885	2.781572	4.30944
	SSLMS	3.524005537	3.57518714	0.4866383	4.320835	1.263397	3.587506	-4.60518	15.7633	4.575355	2.918005	4.071323
	NSSLMS	2.436459408	2.162636177	1.2174812	2.308485	1.093612	1.48109	-9.5382	39.17624	2.956811	1.923487	2.657766
	RLS	4.24414973	4.367047814	0.4427122	4.555533	1.280289	4.185695	-3.20038	4.498804	4.998629	3.429588	4.75238
	GNGD	3.814052157	3.931884289	0.5516608	2.953839	2.15038	2.761439	-7.59594	19.20468	4.639795	2.84414	4.247429
	AP	3.771743153	3.900872135	0.49298	4.826683	3.977229	4.919313	-1.26518	14.64108	4.728315	3.254699	4.27536
	GMCC	3.999579841	4.14240784	0.3979671	2.279699	1.883476	2.658374	-9.93561	22.59472	4.85409	2.761693	4.45174
	OCNLMS	3.813271178	3.927598568	0.5593694	2.61182	1.980314	2.224279	-7.35706	20.41326	4.618365	2.850356	4.234393
	Llncosh	3.797621234	3.915757286	0.4402229	3.38916	2.343154	2.818015	-4.74858	14.47689	4.780977	3.048764	4.324353
	VSLMS_Ang	3.886193446	4.019962205	0.3648063	3.465687	1.890608	3.159651	-3.71339	10.32824	4.906975	3.185359	4.463307
	VSLMS_Ben	3.868969155	3.986145943	0.3441838	3.655455	1.425333	3.259173	-3.5471	9.841892	4.912353	3.191007	4.463405
	VSLMS_Mathews	3.878272258	4.011933515	0.34549	3.653944	2.170976	3.439336	-3.55724	9.408463	4.929726	3.197849	4.473259

Matlab functions		PESQ		LLR	comp_fwseg_mars			composite				
Filter	**Noise Type**	**PESQ Score**	**MOS Score**	**LLR**	**SIG**	**BAK**	**OVL**	**segSNR**	**wss_dist**	**Csig**	**Cbak**	**Covl**
street	LMS	3.772620642	3.891152428	0.5164684	3.561535	1.902861	2.853821	-6.78132	18.88906	4.659955	2.877866	4.234304
	NLMS	3.948018121	4.087241693	0.4003344	3.90116	2.193422	2.896106	-4.03072	12.5642	4.888623	3.179268	4.479234
	LMF	3.939107915	4.075425927	0.5144471	2.612464	1.949365	2.652963	-9.2356	24.17639	4.706293	2.765816	4.33235
	NLMF	4.01454308	4.156112364	0.4568455	2.55878	2.033196	2.354576	-9.17214	21.78311	4.805942	2.822625	4.439321
	SSLMS	3.508599258	3.560929421	0.4630006	4.073528	3.387759	4.362059	-4.43282	18.33119	4.567277	2.903525	4.053048
	NSSLMS	2.343581326	2.125084434	0.9704171	2.750373	2.976773	2.844845	-9.36383	42.83276	3.122126	1.875097	2.693814
	RLS	4.199973961	4.333066903	0.3959923	4.716994	2.191956	4.584624	-3.13101	5.65115	4.996399	3.404776	4.732673
	GNGD	3.837759285	3.962052259	0.5601265	2.599161	2.011879	2.132713	-8.08984	21.36653	4.631176	2.809224	4.247046
	AP	3.716524736	3.833785646	0.4995093	4.941645	4.262822	4.958133	-1.17808	16.53118	4.671289	3.220562	4.214335
	GMCC	3.928856769	4.057860286	0.3232945	2.382674	1.881536	2.591024	-9.8835	23.39916	4.872953	2.725539	4.427409
	OCNLMS	3.8569854	3.987937259	0.4702371	2.811148	2.295719	2.939859	-8.03498	21.06834	4.738354	2.823957	4.310633
	Llncosh	3.821339341	3.949795628	0.4564223	3.518754	2.275267	3.523494	-5.02794	15.36193	4.783454	3.036306	4.328956
	VSLMS_Ang	3.86610869	3.998268541	0.3697	3.857403	1.816405	3.709046	-3.42733	11.34529	4.884424	3.186661	4.437514
	VSLMS_Ben	3.864722511	3.997082955	0.3634069	4.227537	2.433942	4.050599	-3.3485	10.68995	4.899324	3.195552	4.444208
	VSLMS_Mathews	3.834736489	3.969282437	0.3803265	4.450355	2.682925	4.646108	-3.35065	11.19119	4.886919	3.177575	4.407897
train	LMS	3.771613222	3.890274094	0.4567824	3.28412	2.177457	2.200171	-7.13655	20.05382	4.716198	2.846852	4.255899
	NLMS	3.61369369	3.691345489	0.5553948	4.323129	1.508753	2.833093	-3.76725	15.85204	4.557888	3.013045	4.107697
	LMF	3.952237927	4.09321676	0.4763119	2.444587	1.834607	2.093321	-9.53269	22.54578	4.764426	2.76479	4.373859
	NLMF	4.016626251	4.161984578	0.3714596	2.406496	1.894232	2.383162	-9.4557	23.96846	4.879099	2.790459	4.469418
	SSLMS	3.356290898	3.345646314	0.4985653	5	4.149355	5	-4.2763	20.33176	4.420834	2.826578	3.898226
	NSSLMS	2.453730098	2.106465831	0.7716626	3.688416	4.224458	4.235766	-9.40383	43.57681	3.386367	1.909404	2.869124
	RLS	4.073450861	4.22392785	0.4422439	5	1.453218	5	-2.99262	6.99448	4.996839	3.343613	4.597738
	GNGD	3.871037605	4.002760777	0.4627536	2.733434	2.736258	2.517103	-8.44302	22.10379	4.743406	2.797719	4.318529
	AP	3.665193087	3.766531575	0.613231	5	5	4.988329	-1.29499	15.33257	4.534104	3.19705	4.123178
	GMCC	4.041449973	4.185825614	0.3135778	2.442798	2.553678	2.59852	-9.97438	22.44699	4.928229	2.780298	4.529686
	OCNLMS	3.920028306	4.062133645	0.4395712	2.545305	2.161621	2.849034	-8.44628	21.56625	4.802737	2.824694	4.373599
	Llncosh	3.622478225	3.706595768	0.4939674	4.438614	1.662915	3.340509	-4.56847	15.40149	4.625971	2.969921	4.149373
	VSLMS_Ang	3.644099607	3.740664832	0.5318037	4.787139	1.513999	4.108909	-3.09008	12.6898	4.628958	3.092376	4.166388
	VSLMS_Ben	3.64163725	3.733730826	0.5614794	4.717839	2.038658	4.329034	-3.09247	13.49326	4.589706	3.085424	4.143588
	VSLMS_Mathews	3.635082347	3.724647715	0.5515589	4.733802	2.201159	4.39038	-3.18297	13.26371	4.598027	3.078196	4.144997

Appendix 1: Each row is the average result of 30 speech samples (10dB)

Matlab functions		PESQ		LLR	comp_fwseg_mars			composite				
Filter	Noise Type	PESQ Score	MOS Score	LLR	SIG	BAK	OVL	segSNR	wss_dist	Csig	Cbak	Covl
airport	LMS	3.725650291	3.828683853	0.5404167	2.892622	2.18207	2.479372	-6.32511	19.16998	4.610949	2.882189	4.182265
	NLMS	3.938085421	4.083136223	0.3879663	2.742201	2.116016	2.403495	-4.59842	13.41734	4.903	3.132783	4.471599
	LMF	3.881699475	4.01085864	0.4980945	2.531251	2.08074	2.924481	-8.83803	22.01152	4.704139	2.778576	4.309663
	NLMF	3.860622943	3.987499165	0.5237338	2.60326	1.783141	2.338016	-8.9502	24.2926	4.648389	2.745467	4.263602
	SSLMS	3.236891549	3.173243546	0.5374932	3.775093	1.400694	2.325053	-4.75102	19.10509	4.319819	2.748184	3.790766
	NSSLMS	2.081369655	1.758204765	1.8502462	1.154247	1.821588	1.908058	-9.98414	54.797	1.952017	1.616315	1.93784
	RLS	4.074022149	4.219295635	0.497156	4.608715	1.02126	3.365128	-3.26703	5.184433	4.967673	3.339269	4.582753
	GNGD	3.767639344	3.872007888	0.5810802	2.40931	2.150535	1.967591	-7.47361	22.82852	4.561498	2.804295	4.169637
	AP	3.751939695	3.875909241	0.4325489	4.888837	3.525181	4.999266	-1.8908	15.35553	4.772127	3.200818	4.285358
	GMCC	3.799923416	3.91431397	0.3918476	2.532637	2.43588	2.871349	-9.82798	23.68598	4.745537	2.665399	4.286511
	OCNLMS	3.829337438	3.953195324	0.5121468	2.212051	2.123615	2.605705	-7.91452	21.20115	4.679021	2.817401	4.265989
	Llncosh	3.704140641	3.800723872	0.4528997	3.041976	1.615391	2.687916	-5.12087	16.33607	4.701794	2.967612	4.229596
	VSLMS_Ang	3.749895686	3.858046413	0.3874681	3.480045	1.841031	3.164028	-3.96159	12.70601	4.808388	3.087928	4.32534
	VSLMS_Ben	3.754041566	3.866343928	0.3838844	3.771836	1.458847	3.118937	-3.95809	13.11498	4.801106	3.087268	4.32765
	VSLMS_Mathews	3.750364802	3.85475063	0.4097376	3.569144	1.679971	3.154674	-4.09846	13.84172	4.790572	3.071579	4.306366
babble	LMS	3.696186259	3.79464092	0.5528845	2.954092	2.739975	2.808136	-6.55838	19.02924	4.581343	2.854394	4.153148
	NLMS	3.961137569	4.100995214	0.4244092	2.880981	1.655476	2.974953	-4.75036	13.83118	4.879926	3.131333	4.4686
	LMF	3.856892398	3.974624035	0.4652814	3.355386	2.351701	2.860569	-8.69583	25.0255	4.710023	2.754579	4.285396
	NLMF	3.937588489	4.076065685	0.5099266	2.568955	2.086059	2.174664	-8.92158	24.19899	4.723741	2.784715	4.333283
	SSLMS	3.214384259	3.140022321	0.4997079	3.183121	1.59647	2.859307	-4.81182	18.85506	4.347379	2.735346	3.793743
	NSSLMS	2.155887037	1.779682674	1.6898195	1.16936	2.910936	1.199239	-9.96012	54.49405	2.163729	1.655568	2.082843
	RLS	4.091288945	4.235890193	0.4738529	4.126613	1	4.494815	-3.3426	5.172769	4.98418	3.342843	4.608666
	GNGD	3.827263715	3.953815828	0.5603081	2.9428	1.8987	2.620512	-7.68934	21.77947	4.624318	2.826547	4.235613
	AP	3.754278669	3.879806636	0.4481595	4.918027	3.768353	4.822679	-2.10386	14.92452	4.761353	3.191531	4.282265
	GMCC	3.903099639	4.034274607	0.3628001	3.240097	2.421228	2.85352	-9.90542	22.15663	4.832256	2.720543	4.395145
	OCNLMS	3.788144242	3.908819847	0.5146665	2.528691	1.791662	2.347328	-7.60345	23.2816	4.630895	2.802744	4.216976
	Llncosh	3.683898721	3.778935478	0.4961179	3.393348	2.088312	3.159077	-5.48483	18.02333	4.641676	2.923196	4.179363
	VSLMS_Ang	3.727309067	3.839347257	0.406091	3.50534	1.78351	3.342372	-4.09795	13.10981	4.793623	3.065714	4.294797
	VSLMS_Ben	3.709525298	3.810689381	0.4079809	4.048389	1.761123	3.484886	-4.11023	13.18367	4.770026	3.055923	4.278996
	VSLMS_Mathews	3.739605272	3.846311988	0.395996	3.58552	1.521502	3.855105	-4.08908	13.4224	4.788534	3.069963	4.307676

Matlab functions		PESQ		LLR	comp_fwseg_mars			composite				
Filter	**Noise Type**	**PESQ Score**	**MOS Score**	**LLR**	**SIG**	**BAK**	**OVL**	**segSNR**	**wss_dist**	**Csig**	**Cbak**	**Covl**
car	LMS	3.726040284	3.824720321	0.535063	2.479113	2.17946	2.337324	-7.08622	19.38589	4.612596	2.832914	4.183809
	NLMS	3.947592821	4.086431155	0.3538736	2.07651	1.885504	2.483626	-4.59055	12.90926	4.934462	3.14138	4.500264
	LMF	3.938185304	4.07933724	0.4020386	2.959952	2.184033	3.156202	-9.1279	21.81401	4.828651	2.788697	4.405697
	NLMF	3.977000974	4.121468422	0.4376774	2.665079	2.088377	1.99785	-9.33234	23.49083	4.811507	2.782633	4.406959
	SSLMS	3.30656863	3.276298488	0.4468593	3.734281	2.572226	4.302387	-4.84903	17.8681	4.46623	2.783974	3.901919
	NSSLMS	2.15483296	1.807507564	1.266317	2.000547	1.25896	1.648399	-9.92821	46.97907	2.666512	1.70968	2.351433
	RLS	4.189202542	4.323624205	0.4113529	4.512625	1.543879	4.837926	-3.50941	5.199062	4.998497	3.378952	4.719302
	GNGD	3.86450109	3.99648787	0.5129391	2.667437	2.064007	1.996826	-8.29929	19.63727	4.708011	2.820915	4.304838
	AP	3.776593852	3.906302345	0.5220571	4.810328	4.292044	4.962626	-1.75513	15.22933	4.696025	3.222033	4.26026
	GMCC	3.923745326	4.059365368	0.354614	2.304661	2.423346	2.505118	-9.95355	21.7873	4.848035	2.729966	4.418542
	OCNLMS	3.793843866	3.910234393	0.5063375	2.730398	2.0411	2.783899	-8.40753	21.73677	4.662344	2.765626	4.236642
	Llncosh	3.787940737	3.915013778	0.4338249	3.491551	2.071808	3.109367	-5.75847	14.90494	4.790792	2.977517	4.316839
	VSLMS_Ang	3.797484668	3.919258544	0.3661189	2.941379	1.810276	3.60594	-4.20899	12.68011	4.853282	3.09527	4.374762
	VSLMS_Ben	3.828279146	3.953114443	0.3407305	3.243013	1.923018	3.800126	-4.11414	11.99478	4.888814	3.120763	4.417347
	VSLMS_Mathews	3.797195005	3.920086777	0.3596023	3.148849	2.029346	3.872065	-4.21877	12.86603	4.851642	3.093215	4.376563
exhibition	LMS	3.736234364	3.840629671	0.5163364	2.312604	1.976454	2.033012	-7.62519	20.22176	4.632552	2.79798	4.195752
	NLMS	3.868700014	3.999104322	0.3822146	3.638195	1.777912	3.223065	-4.0594	14.34945	4.861447	3.12705	4.412163
	LMF	3.880495714	4.003604796	0.5051674	2.602106	2.10876	2.755862	-9.28815	23.80349	4.691463	2.737099	4.292529
	NLMF	3.946802403	4.086722564	0.4596865	2.540555	1.95962	2.650615	-9.39989	23.1385	4.7824	2.766409	4.373847
	SSLMS	3.258259673	3.204389739	0.4692327	4.921601	4.683933	5	-4.78371	20.62306	4.389283	2.745713	3.83229
	NSSLMS	2.107492679	1.746328997	1.1732097	2.711817	2.678118	3.223023	-9.94394	55.02906	2.661324	1.62971	2.304645
	RLS	4.106340502	4.252515714	0.4281117	4.975039	1.426935	5	-3.49874	5.82932	4.996065	3.335605	4.639606
	GNGD	3.82218556	3.948471849	0.4892535	2.464541	2.158878	2.540108	-8.56654	22.11797	4.69008	2.766487	4.265536
	AP	3.747934529	3.870693462	0.5201522	4.782308	4.066667	4.631472	-1.77926	16.07759	4.67307	3.200876	4.232226
	GMCC	3.891360256	4.019165192	0.338914	3.087482	2.62056	2.672016	-9.91535	21.50599	4.843272	2.718861	4.402479
	OCNLMS	3.833116098	3.962074513	0.4707833	2.758721	2.13204	2.355381	-8.74712	23.40021	4.707726	2.751359	4.274816
	Llncosh	3.68858849	3.786205187	0.4692135	3.162552	2.415219	2.980619	-6.04297	17.98172	4.662858	2.890566	4.197204
	VSLMS_Ang	3.750389995	3.861764617	0.3892793	3.637314	2.270313	4.184943	-4.27966	13.23913	4.811403	3.064394	4.321079
	VSLMS_Ben	3.749583967	3.864056866	0.3905186	4.166289	1.963098	4.071049	-4.373	13.81644	4.806868	3.054087	4.315755
	VSLMS_Mathews	3.780204558	3.893097934	0.4165641	3.781625	1.953768	3.977959	-4.41646	13.63108	4.79408	3.067283	4.328366

Matlab functions		PESQ		LLR	comp_fwseg_mars			composite				
Filter	Noise Type	PESQ Score	MOS Score	LLR	SIG	BAK	OVL	segSNR	wss_dist	Csig	Cbak	Covl
restaurant	LMS	3.731938502	3.837161345	0.5456303	2.617469	2.076328	2.796914	-6.60545	18.73212	4.611628	2.870598	4.187723
	NLMS	3.935077368	4.072738355	0.4165172	3.065308	1.8532	2.923899	-4.74858	13.16894	4.865784	3.123624	4.456298
	LMF	3.860477613	3.984096211	0.4789457	2.694273	2.134725	2.730525	-8.73321	23.17441	4.696577	2.766895	4.294243
	NLMF	3.93894042	4.078549644	0.4908353	2.696984	2.278177	1.826052	-8.81619	23.67681	4.73848	2.795656	4.347802
	SSLMS	3.211422952	3.13565756	0.4721726	3.814982	3.478015	3.554482	-4.82735	20.06567	4.363031	2.724478	3.796983
	NSSLMS	2.037068299	1.704483911	1.6879111	1.467177	2.13333	3.024087	-9.98118	57.05693	2.072451	1.580515	1.975691
	RLS	4.094175978	4.236712704	0.4355622	4.793344	1.214071	4.111906	-3.37064	5.250218	4.991143	3.341915	4.630052
	GNGD	3.791932599	3.908443832	0.5269307	2.178501	2.375307	2.239216	-7.96038	21.13755	4.644703	2.797077	4.228754
	AP	3.76360774	3.891160564	0.4569915	4.963165	3.191652	4.83067	-2.05721	15.38415	4.753754	3.195711	4.282036
	GMCC	3.900894173	4.031067557	0.3878553	2.505915	1.791293	2.777993	-9.87499	24.84314	4.796776	2.702601	4.361736
	OCNLMS	3.754233213	3.862180151	0.5284732	3.295824	1.936476	2.567795	-7.69941	22.20436	4.60574	2.78803	4.190149
	Llncosh	3.726869895	3.832465745	0.4882216	3.235582	2.166811	3.165076	-5.35318	17.08656	4.677878	2.958587	4.224555
	VSLMS_Ang	3.724627028	3.825968801	0.4120239	3.886619	1.733096	3.411342	-4.10493	13.05341	4.77225	3.064387	4.289995
	VSLMS_Ben	3.70476636	3.806162509	0.4060467	3.646503	1.547424	3.670624	-4.09483	14.23677	4.763127	3.047246	4.268784
	VSLMS_Mathews	3.772979585	3.883171566	0.3878097	3.556858	1.607985	3.571443	-4.08065	13.06676	4.821303	3.088936	4.341223
station	LMS	3.65179092	3.736430239	0.555067	2.967072	2.157426	2.929772	-6.82457	20.16192	4.542409	2.808475	4.108364
	NLMS	4.006608835	4.153442638	0.4130265	2.877229	1.996949	2.257359	-4.78902	13.14059	4.923309	3.155467	4.515866
	LMF	3.931443635	4.071734336	0.4595888	3.154568	2.138664	2.139549	-8.88882	23.73074	4.77161	2.787119	4.357387
	NLMF	3.95620709	4.101413012	0.4323105	2.932009	2.123494	2.679954	-9.02908	23.30649	4.793889	2.79309	4.394258
	SSLMS	3.317963793	3.2900316	0.484952	4.476277	1.265974	2.783658	-4.80949	17.08244	4.440975	2.797412	3.897088
	NSSLMS	2.223962734	1.857663195	1.5687952	1.708615	1.201021	1.607782	-9.94493	47.98507	2.387894	1.734628	2.245171
	RLS	4.133023571	4.273974999	0.4746992	4.691519	1.106368	3.673035	-3.35269	4.907196	4.992771	3.364015	4.643688
	GNGD	3.851453916	3.982512296	0.4920467	2.344682	2.154341	2.322082	-7.86042	20.92192	4.710852	2.833335	4.296039
	AP	3.782788663	3.912062078	0.459167	4.960944	4.123271	4.922008	-1.76461	15.15609	4.765134	3.22491	4.297959
	GMCC	3.875967481	3.9987606	0.3839831	2.537806	2.092946	2.951333	-9.86054	20.78493	4.808907	2.720004	4.37206
	OCNLMS	3.807006831	3.929452819	0.5589837	2.957232	2.117763	2.712774	-7.97587	23.02818	4.606177	2.790072	4.211244
	Llncosh	3.732287645	3.839873779	0.5261754	3.358496	1.961326	3.341688	-5.42805	16.63277	4.644534	2.959637	4.21266
	VSLMS_Ang	3.811163474	3.933134626	0.4066982	3.530384	1.558314	3.598688	-4.02733	12.87501	4.832102	3.11189	4.363632
	VSLMS_Ben	3.764694116	3.877026165	0.3773178	3.818462	2.118169	3.410604	-4.05454	13.28323	4.832332	3.085105	4.338409
	VSLMS_Mathews	3.790185866	3.913915808	0.401937	3.676092	1.544641	3.775308	-4.11516	12.89722	4.836931	3.096173	4.349027

Matlab functions		PESQ		LLR	comp_fwseg_mars			composite				
Filter	Noise Type	PESQ Score	MOS Score	LLR	SIG	BAK	OVL	segSNR	wss_dist	Csig	Cbak	Covl
street	LMS	3.701396983	3.795376314	0.5360104	2.746533	2.279207	2.30818	-7.29737	19.45353	4.598231	2.807359	4.163013
	NLMS	3.916486229	4.055874777	0.4275431	3.694816	1.967021	2.82856	-4.39291	14.47639	4.86439	3.127992	4.426535
	LMF	3.905257395	4.040881537	0.4766768	2.839844	1.907374	2.267522	-9.38784	23.01634	4.742324	2.748165	4.332559
	NLMF	3.975458132	4.117860137	0.4812188	2.679007	2.098967	3.203775	-9.33435	22.81445	4.768846	2.786504	4.388159
	SSLMS	3.264198976	3.215275365	0.4601145	4.208166	3.613488	4.34867	-4.79506	19.80757	4.409586	2.753545	3.847449
	NSSLMS	1.976793576	1.717212086	1.3364357	2.109459	1.861377	2.215052	-9.9121	54.22762	2.421766	1.59812	2.154018
	RLS	4.134150848	4.274002046	0.4309479	4.905376	1.79321	4.737472	-3.47142	5.901898	4.989468	3.350111	4.660033
	GNGD	3.828200364	3.953543914	0.4841104	2.606887	2.408983	2.412343	-8.36908	21.28436	4.703556	2.787637	4.278846
	AP	3.773207101	3.901874556	0.4812314	4.970765	3.591711	4.848642	-1.75461	15.98577	4.729185	3.215152	4.273141
	GMCC	3.9105296	4.040051841	0.3382095	2.966555	2.195094	2.470185	-9.91774	24.47516	4.848163	2.707089	4.397487
	OCNLMS	3.819766152	3.947213031	0.4798975	2.614203	2.230346	2.54818	-8.61276	23.4215	4.686703	2.753294	4.259254
	Llncosh	3.674699479	3.764681695	0.4995609	3.097809	2.116615	2.853377	-5.88311	17.80306	4.633947	2.895249	4.171737
	VSLMS_Ang	3.752420304	3.869094612	0.3899263	4.07671	2.046633	3.532758	-4.355	13.61129	4.817021	3.058013	4.319777
	VSLMS_Ben	3.738949178	3.847434077	0.4026079	4.153234	2.067692	3.860685	-4.413	14.60963	4.777501	3.040931	4.295451
	VSLMS_Mathews	3.77032192	3.886975191	0.390755	3.824921	2.033865	3.523132	-4.29179	13.40123	4.821034	3.072022	4.335234
train	LMS	3.68992581	3.788090721	0.4889121	2.873191	2.15605	2.855715	-8.12527	20.57165	4.624253	2.741891	4.170066
	NLMS	3.626381431	3.710340728	0.5331964	4.037123	1.602755	2.618987	-4.10134	16.18587	4.585376	2.995725	4.126939
	LMF	3.874938457	4.001540506	0.4596475	2.807719	2.412268	2.72503	-9.387	24.27666	4.726243	2.724903	4.308049
	NLMF	3.962124938	4.104665774	0.4479255	2.743102	1.920411	2.179923	-9.52771	24.54739	4.78918	2.755818	4.382341
	SSLMS	3.210284895	3.134665116	0.4864128	4.953532	3.551497	5	-4.74372	20.91926	4.34001	2.723227	3.782801
	NSSLMS	2.031589717	1.689369034	1.0385946	3.020144	2.891489	3.023171	-9.90896	52.89257	2.773302	1.610587	2.327421
	RLS	4.085317548	4.23466002	0.4588237	5	1.266667	5	-3.50242	6.751609	4.991868	3.318868	4.600502
	GNGD	3.874430368	4.005380462	0.4814757	2.614512	2.206384	2.72567	-8.95145	23.36187	4.720007	2.758503	4.302868
	AP	3.706675611	3.82137238	0.5905488	4.867438	4.424881	4.929145	-1.97512	15.42006	4.58167	3.173418	4.167572
	GMCC	3.875422927	4.010768599	0.3493425	2.611127	2.82973	2.753629	-9.96785	24.54253	4.822645	2.68668	4.363054
	OCNLMS	3.832813054	3.963422518	0.508677	2.640107	2.334026	2.179587	-9.1138	22.33842	4.677925	2.735547	4.262603
	Llncosh	3.663888392	3.757210123	0.4591485	3.383553	1.949346	3.03242	-6.42297	17.02821	4.673861	2.861494	4.189149
	VSLMS_Ang	3.68484212	3.785879247	0.4231766	4.419428	2.425626	4.231164	-4.2289	13.72013	4.751244	3.032893	4.247591
	VSLMS_Ben	3.664042733	3.763315023	0.4481182	4.453066	1.451021	3.512373	-4.32394	14.03436	4.714995	3.014764	4.215877
	VSLMS_Mathews	3.659317612	3.756458713	0.4714151	4.809162	2.358698	4.301817	-4.38503	13.78226	4.689603	3.010421	4.20191

LIST OF PUBLICATIONS−MANUSCRIPT

Ensemble-Based Adaptive Filtering for Speech Enhancement in Car Noise Conditions

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Abstract. In-car noise due to engine vibrations, road friction, and external disturbances considerably impairs the performance of speech communication systems. This paper presents an ensemble-based adaptive filtering system to enhance the quality of speech in such in-car noisy conditions. The suggested method is a combination of the outputs of three adaptive filters-Normalized Least Mean Squares (NLMS), Variable Step-Size LMS (VSLMS) with Mathews' adaptation, and Generalized Maximum Correntropy Criterion (GMCC) by dynamic error-based weighting, in which lower error filters are given greater influence in every iteration. Post-processing methods, such as noise estimate subtraction, pre-emphasis, and de-emphasis, further enhance the output to minimize residual noise. The In-Car noisy speech samples at 5dB & 10dB SNR are sourced from the NOIZEUS speech corpus for performance testing. Objective measures of speech quality, such as PESQ (Perceptual Evaluation of Speech Quality), LLR (Log-Likelihood Ratio), fwsegSNR (frequency-weighted segmental SNR), and COVL (Composite Objective Measure), were employed to measure system performance. The results show that the ensemble-based method robustly outperforms individual filters and static combination methods, providing an effective solution for car noise conditions in real-time speech enhancement.

Keywords: Adaptive Filter, Ensemble, NOIZEUS, SNR, Pre-Emphasis, De-Emphasis, PESQ, LMS, RLS

Introduction

Noisy speech improvement is important in order to improve communication quality in various applications like mobile communication, car voice assistants, and hearing aids. Automotive environments involve much engine, tire, and other noise background which badly deteriorates the quality and intelligibility of the speech signals. The challenge to real-time systems is that this should be efficiently carried out without introducing substantial latency or distortion.

Conventional adaptive filters such as Recursive Least Squares (RLS) [1] and Normalized Least Mean Squares (NLMS) [2] have been traditionally used for filtering out noise. The filters, however, cannot maintain stable operation in dynamic environments of noise, especially in the case of car-type environments in which the environment of the noise tends to frequently change. RLS filter's requirement of large amounts of computations also makes it unsuitable for low power-embedded applications, which motivates the formulation of energy-effective substitutes.

Individual adaptive filters tend not to adapt optimally to different noise profiles and, as such, result in unreliable speech improvement. While RLS is more accurate, its high computational cost makes it infeasible for low power real-time applications, particularly for resource-limited environments. For these limitations, an ensemble-based strategy that employs a set of adaptive filters is capable of enhancing robustness by dynamically varying filter contributions according to their respective error performance.

In automobile settings, speech enhancement is difficult because of non-stationary noise from sources including traffic, wind, and engines. The early methods employed multi-channel adaptive Wiener filtering for high-frequency sub-bands [3] and spectral subtraction for low-frequency sub-bands to reduce noise and distortion [4]. In speech presence estimation, sub-band-based methods later surpassed more traditional methods such as Wiener and MMSE-based estimators [5]. To compensate speech enhancement for various conditions, environment-adaptive techniques brought in sub-band processing and statistical modeling. A robust system enhanced speech recognition with time- and frequency-domain beamformers without retraining in diverse environments [6].

Later, dynamic multi-microphone systems with power ratio-based controls were developed to control multiple talkers and ambient noise [7]. With pipelined architectures, real-time capability was delivered by psychoacoustic models and perceptual filter banks [8]. Real-time adaptive Wiener filters and blind source separation (BSS) techniques further augmented noise cancellation in automotive environments [9].

Later developments utilized adaptive parallel filter methods to dynamically suppress road noise and beamforming combined with Kalman filtering for enhanced intelligibility [10]. Time difference of arrival (TDOA) and source separation with microphone arrays [11] were examined in recent studies for adaptive signal adjustment. Norm-based adaptive filters provided robust solutions for channel estimation and in-car echo cancellation [12]. Yet, existing methods often lack in dynamically responding to changing noise patterns and have difficulty in balancing computational complexity and noise reduction. Whereas methods such as spectral subtraction and Wiener filtering fail in non-stationary environments, methods such as RLS are effective but computationally expensive.

This research aims to develop an ensemble-based adaptive filtering system for speech enhancement in car noise environments. A performance-based dynamic weighting scheme will adaptively regulate the contribution of multiple adaptive filters, ensuring improved noise attenuation with low computational complexity, making it ideal for real-time applications in challenging automotive environments.

This manuscript is structured in following sections. Section 2 describes the methodology, including pre and post processing, parallel adaptive filtering, and dynamic weight assignment. Section 3 elucidates the experimental setup. Results are shown in section 4, followed by Section 5 discussing the conclusions and future directions.

Methodology

Model Diagram

Figure 1 shows the proposed ensemble adaptive filter system, that pre-emphasizes a noisy speech signal after noise estimate subtraction. Three parallel adaptive filters-NLMS [2], GMCC [13], and VSLMS (Mathew's) [14] process the pre-emphasized signal. The enhanced speech signal is produced by dynamically combining the filter outputs and de-emphasizing the resultant signal.

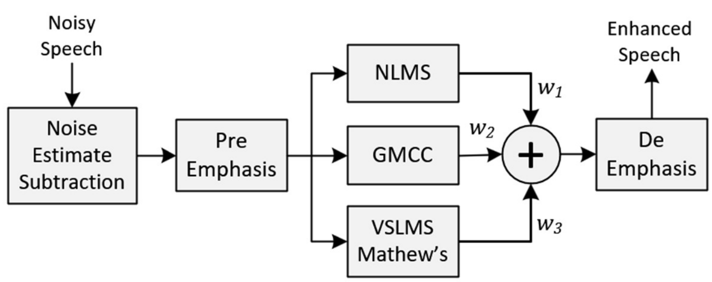

Fig. 1. Block diagram of the proposed ensemble-based adaptive filtering system model for speech enhancement in car noise environment

Pre-Processing

The noisy speech signal is conditioned during the pre-processing phase by noise estimate subtraction and pre-emphasis. The pre-computed noise profile is obtained by averaging the differences between 30 noisy and their corresponding 30 clean speech samples available in the dataset. In the frequency domain, the estimate noise spectrum is subtracted from signals spectrum, and the signal is converted back by IFFT. The pre-emphasis is the following step, where high-frequency components are boosted to preserve the speech details. All of these processes assure that input is optimized to provide efficient speech enhancement and attenuation of noise is supplied to the filters.

Parallel Filtering

Here we are applying three adaptive filters in parallel: NLMS, GMCC, and VSLMS (Mathew's). In our preliminary analysis, it was found that these filters showed exceptional individual performance in Car noise conditions. These were sourced from python Padasip library [15]. Each filter iteratively updates its weights using a different adaptation rule. NLMS uses normalized step-size control to improve stability and convergence speed. GMCC employs a kernel-based method to enhance error minimization by accounting for higher-order dependencies. VSLMS (Mathew's) dynamically adjusts the step-size according to the error magnitude, allowing for better trade-offs between convergence speed and steady-state error.

Dynamic weight assignment & post-processing

To enhance speech robustness, an error-based dynamic weight assignment strategy combines outputs from three parallel adaptive filters. Each filter's error—defined as the difference between the desired clean signal and its output—guides weight adjustments. Filters with smaller errors are given higher weights, while less accurate ones contribute less. A normalized inverse error measure continuously updates these weights, ensuring the most effective filter dominates the final signal. Once combined, the output undergoes post-processing: de-emphasis reverses the high-frequency boost applied earlier to restore spectral balance, and normalization adjusts the amplitude to maintain clarity and prevent distortion.

Experimental Setup

Dataset

We use the NOIZEUS Speech Corpus [16], which contains 30 IEEE sentences in American English from three male and three female speakers. It includes eight noise types from the AURORA database, with a focus on car noise at 5 dB and 10 dB SNR levels. Noise was synthetically added following ITU-T P.56 to achieve the desired SNR levels.

Performance parameters

The ensemble filter's performance was assessed using the following objective speech quality metrics, selected due to their high correlation with subjective ratings [17].

Perceptual Evaluation of Speech Quality (*PESQ*):
The ITU-T P.862 standard defines (PESQ) [18] parameter. Using an auditory model, it compares the clean and enhanced signals to determine speech quality. The PESQ metric is computed as follows:

$$PESQ = a_0 D_t + a_1 D_a + a_2 \tag{1}$$

D_t and D_a are the disturbance values in this. For speech communication network system, the regression coefficients a_0, a_1 and a_2 are optimized. The PESQ scores range from -0.5 to 4.5 where better speech is an indication of a high score values.

Log Likelihood Ratio (*LLR*):
LLR measures spectral distortion. It compares the Linear Predictive Coding (LPC) coefficients [17] of clean and enhanced speech. It is defined as:

$$d_{LLR}(b_p, b_c) = \log\left(\frac{b_p Q_c {b_p}^T}{b_c Q_c {b_c}^T}\right) \quad (2)$$

Where $d_{LLR}(b_p, b_c)$ is the LLR distance. The original clean speech frame's LPC coefficient vector is denoted by b_c. The processed speech frame's LPC coefficient vector is denoted by b_p. The original speech signal's autocorrelation matrix is denoted by Q_c. The range of values was limited to (0, 2). Better spectrum preservation and less distortion are indicators of a low LLR value.

Frequency-Weighted Segmental Signal-to-Noise Ratio (fwsegSNR):
It measures how well noise is suppressed. Segmental SNR [17] is averaged across frequency bands. It is computed as follows:

$$fwsegSNR = \frac{10}{N} \cdot \sum_{m=0}^{N-1} \frac{\sum_{j=1}^{B} W(j,m) \log_{10}\left(\frac{|Y(j,m)|^2}{\left(|Y(j,m)| - |\hat{Y}(j,m)|\right)^2}\right)}{\sum_{j=1}^{B} W(j,m)} \quad (3)$$

Here, N is the total number of frames, B is the number of bands, and $W(j,m)$ is a frequency-domain weighting function that assigns higher importance to speech-dominant regions. It is proportional to the clean speech spectrum raised to a power γ, i.e., $W(j,m) = Y(j,m)^{\gamma}$. The clean and enhanced speech spectrums are represented by $|Y(j,m)|$ and $|\hat{Y}(j,m)|$, respectively. The signal bandwidth was divided into 25 critical bands corresponding to auditory perception [18]. Better speech intelligibility is correlated with higher *fwsegSNR* values.

Composite Speech Quality Measure (C_{OVL}):
The composite measure is created as a weighted sum of a number of objective measures [17] for a more reliable estimate of speech quality. It is given as:

$$C_Y = \alpha_0 + \sum_{n=1}^{N} \alpha_n M_n \quad (4)$$

Here, C_Y represents the composite score (e.g., for speech distortion or overall quality), α_n are regression coefficients, and M_n are objective metrics. We consider the overall quality (OVL) component in our analysis. Using multiple measures improves correlation with subjective ratings, enhancing evaluation robustness.

Results & Discussion

The Composite Objective Measure (C_{OVL}) of each speech sample was examined, as it most closely correlates with subjective ratings of speech quality. Figure 2 present the C_{OVL} scores of all 30 speech samples for both 5 dB and 10 dB SNR. The per-sample result indicates that, for the 5 dB SNR input samples, NLMS has slightly better C_{OVL} values in just 5 out of 30 samples, whereas under the 10 dB SNR condition, this is true for 4 out of 30 samples. Table 1 presents the average value of the performance parameters for all 30 noisy input speech samples for each filter tested. The Ensemble can be seen to have the highest C_{OVL} values.

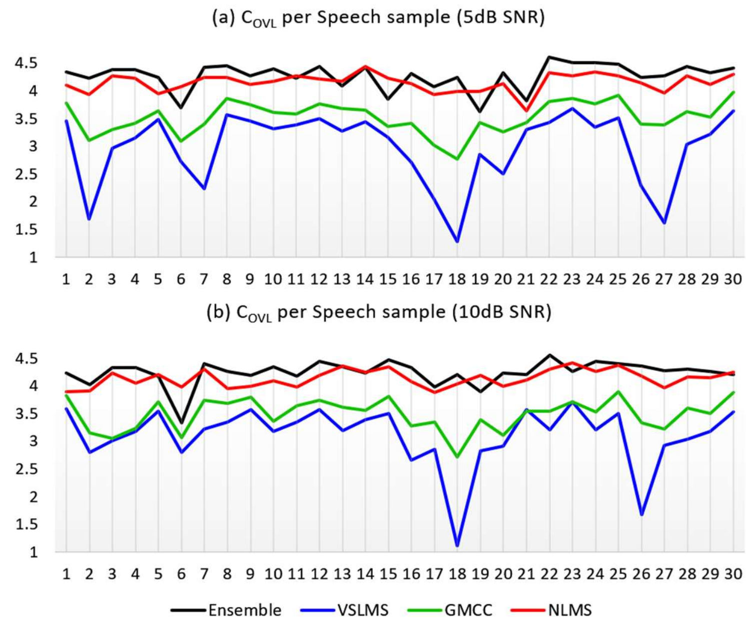

Fig. 2. C_{OVL} values per speech sample for each filter tested at (a) 5dB & (b) 10dB SNR

Table 1. Average values of performance parameters for each filter tested at 5dB & 10dB SNR speech samples

S. No.	Filter	Performance Parameters							
		for Speech samples at 5dB SNR				*for Speech samples at 10dB SNR*			
		PESQ	***LLR***	***fwsegSNR***	***C_{OVL}***	***PESQ***	***LLR***	***fwsegSNR***	***C_{OVL}***
1	NLMS	3.75	0.77	1.27	4.15	3.76	0.82	1.36	4.14
2	$VSLMS_{Mathews}$	2.43	0.91	1.91	2.98	2.65	0.99	1.79	3.11
3	GMCC	3.14	0.97	1.74	3.52	3.15	1.04	1.97	3.49
4	Ensemble	3.58	0.28	2.13	4.27	3.60	0.36	1.81	4.24

Conclusions & Future Work

The proposed ensemble-based adaptive filtering method was compared with standalone filters. While averaged PESQ values suggested that NLMS was marginally better, a detailed per-sample comparison of C_{OVL}, which correlates very well with listening tests, demonstrated that the ensemble approach performed better in 26 out of 30 samples under 10dB and 25 out of 30 samples under 5dB. This indicates that, overall, the ensemble method steadily enhances speech quality. Future work could further enhance the ensemble method's robustness and flexibility by integrating psychoacoustic models or fuzzy logic to enhance the dynamic weight assignments.

References

1. Venkateswarlu SC, Kumar NU, Karthik A. Speech enhancement using recursive least square based on real-time adaptive filtering algorithm. In: 2021 6th International Conference for Convergence in Technology (I2CT). IEEE; 2021 Apr 2. p. 1–4.
2. P. S. R. Diniz. Adaptive Filtering: Algorithms and Practical Implementation. Cham: Springer International Publishing; 2020. doi: 10.1007/978-3-030-29057-3.
3. Chen YH, Ruan SJ, Qi T. An automotive application of real-time adaptive Wiener filter for non-stationary noise cancellation in a car environment. In: 2012 IEEE International Conference on Signal Processing, Communication and Computing (ICSPCC). IEEE; 2012 Aug 12. p. 597–601.

4. Visser E, Lee T, Otsuka M. Speech enhancement in a noisy car environment. In: Proc. 3rd International Conference on Independent Component Analysis and Source Separation. 2001 Dec. p. 272–7.
5. Fingscheidt T, Suhadi S, Stan S. Environment-optimized speech enhancement. IEEE Transactions on Audio, Speech, and Language Processing. 2008 Apr 15;16(4):825–34.
6. Ramesh Babu G, Sridhar GV. Speech enhancement using beamforming and Kalman Filter for In-Car noisy environment. In: Microelectronics, Electromagnetics and Telecommunications: Proceedings of the Fifth ICMEET 2019. Springer Singapore; 2020 Jun 24. p. 549–57.
7. Matheja T, Buck M, Fingscheidt T. A dynamic multi-channel speech enhancement system for distributed microphones in a car environment. EURASIP Journal on Advances in Signal Processing. 2013 Dec;2013:1–21.
8. Yang CH, Wang JC, Wang JF, Wu CH, Chang KH. Design and implementation of sub-space-based speech enhancement under in-car noisy environments. IEEE Transactions on Vehicular Technology. 2008 May 16;57(3):1466–79.
9. Djendi M. An efficient frequency-domain adaptive forward BSS algorithm for acoustic noise reduction and speech quality enhancement. Computers & Electrical Engineering. 2016 May 1;52:12–27.
10. Yin L, Zhang Z, Wu M, Wang Z, Ma C, Zhou S, Yang J. Adaptive parallel filter method for active cancellation of road noise inside vehicles. Mechanical Systems and Signal Processing. 2023 Jun 15;193:110274.
11. Pathrose J, Govindaraj V. In-Car Speech Enhancement Based on Source Separation Technique. Audiology and Speech Research. 2024 Jul 31;20(3):172–82.
12. Huang X, Li Y, Han X, Tu H. Lawson-norm-based adaptive filter for channel estimation and in-car echo cancellation. IEEE Transactions on Circuits and Systems II: Express Briefs. 2022 Jan 25;69(4):2376–80
13. Chen B, Xing L, Zhao H, Zheng N, Prı JC. Generalized correntropy for robust adaptive filtering. IEEE Transactions on Signal Processing. 2016 Mar 7;64(13):3376–87.
14. Mathews VJ, Xie Z. A stochastic gradient adaptive filter with gradient adaptive step size. IEEE Transactions on Signal Processing. 1993 Jun;41(6):2075–87.
15. Cejnek M, Vrba J. Padasip: An open-source Python toolbox for adaptive filtering. Journal of Computational Science. 2022 Nov 1;65:101887.
16. Hu Y, Loizou PC. Subjective comparison and evaluation of speech enhancement algorithms. Speech Communication. 2007 Jul 1;49(7-8):588–601.
17. Hu Y, Loizou PC. Evaluation of objective quality measures for speech enhancement. IEEE Transactions on Audio, Speech, and Language Processing. 2007 Dec 18;16(1):229–38.
18. Loizou PC. Speech enhancement: Theory and practice. CRC Press; 2007 Jun 7.

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Education

Degree	Institute	Percentage	Year
M.Tech. ECE	Delhi Technological University (DTU)	85%	*2023-2025*
B.Tech. ECE	Inderprastha Engineering College (AKTU)	86.8%	*2019-2023*
Intermediate	KGDS SVM (CBSE)	82%	*2016-2018*
High School	KGDS SVM (CBSE)	91.2%	*2014-2016*

Internship

- **Samsung Semiconductor India Research** — Bangalore
  Student Trainee – Digital IP Development, Foundry Division — *August 2024 – Present*
  - Worked on digital controller design for **PLL IP**, covering the complete **front-end VLSI flow**.
  - Performed **RTL design**, simulation (Cadence Xcelium), lint checks (SpyGlass), and logic synthesis (Synopsys Design Compiler).
  - Wrote **SDC constraints**, conducted **DFT tasks** (scan insertion, ATPG), and analyzed test coverage.
  - Conducted **Formality checks**, used **GCA** for SDC quality, and studied **pre-layout STA** and **Gate-Level Simulation (GLS)**.
  - **Tools:** Cadence Xcelium, Synopsys SpyGlass, Design Compiler, Formality, GCA
  - **Skills:** RTL, Synthesis, Constraints, DFT, Equivalence Checking, STA, GLS, TCL scripting, Linux, gvim

- **Indian Institute of Technology, Bombay** — Remote
  FOSSEE Summer Fellowship (eSim) — *May 2022 – September 2022*
  - **Analog Circuit Design**: Integrated Circuit Model using subcircuit feature of eSim.
  - **IC Model**: LM321 Operational Amplifier, LM13700 Operational Trans-conductance Amplifier, LM723 Adjustable Voltage Regulator...
  - **Test Circuits**: Non-Inverting Amplifier, Schmitt Trigger, Voltage Comparator, Amplitude Modulator, Voltage Controlled Amplifier, Voltage Regulator...

Projects

- **Design of 32-Bit Pipelined RISC Processor**: Using MIPS32 ISA, implemented a 5 Stage Pipelined RISC Microprocessor Architecture on Verilog.
- **4-Bit LFSR Design on 90nm**: Designed on 90nm CMOS Technology using Cadence Virtuoso tool, using custom made symbols such as positive edge triggered D flip-flop with asynchronous set, Buffers, Inverters etc.
- **Toffoli's Quantum Gate Circuit Design on 130nm**: Designed on 130nm CMOS Technology using open-source EDA tool eSim & Sky130 PDK, under circuit simulation project of FOSSEE 2022 fellowship program.
- **Schmitt Trigger Design on 28nm**: Designed on 28nm CMOS Technology using Synopsys custom compiler tool as part of Analog IC design hackathon, performed Transient and DC analysis.

Publications

- **"IoT Applications in Bio-Medical Systems" (IoT, RFID)**: Published in International Journal of Radio Frequency Design, Vol. 7, Issue 1 (2021) | Journals Pub

Skills

- **Languages**: C, Python & OOPS
- **HDL**: Verilog,VHDL
- **Tools**: Cadence Virtuoso, Xilinx Vivado, ISE, MATLAB, Modelsim, eSim
- **Interest**: CMOS Digital design, FPGA design, Basic STA
- **Soft Skills**: Team Player, Verbal & Written Communication, Presentation, Time Management
- **Others**: Microprocessors, Signal Systems, Digital Signal Processing, Signal Integrity for High Speed Digital Designs
- **Certifications**: Digital Circuits, System Design through Verilog, HDLs for FPGA Design, Python for Everybody

Awards

- **Hackathon Winner** - Cloud based Analog IC Design Hackathon organised by Synopsys & IIT Hyderabad.
- **Hackathon Winner** - Capture the Bug, Design Verification Hackathon by NIELIT & IIT Madras.