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Wei-Chen Lin
Department of Electrical Engineering and Signal Processing, Taipei Institute of Technology, Taipei, Taiwan

Corresponding Author:
Wei-Chen Lin
Department of Electrical Engineering and Signal Processing, Taipei Institute of Technology, Taipei, Taiwan

Discrete Fourier transform based noise reduction in audio signals

Wei-Chen Lin

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Abstract
Audio signal quality degradation due to background noise remains a persistent challenge across communication, broadcasting, and recording industries. This research presents a spectral subtraction approach for noise reduction utilizing the Discrete Fourier Transform to separate noise components from desired audio content in the frequency domain [1]. The methodology transforms time-domain signals into frequency representations where noise characteristics can be estimated during speech pauses and subsequently subtracted from the composite spectrum. Implementation employed 2048-point DFT windows with 50% overlap and Hann windowing to minimize spectral leakage effects [2]. Testing across six distinct noise types revealed signal-to-noise ratio improvements ranging from 8.4 dB for impulsive noise to 29.4 dB for periodic hum contamination at 50/60 Hz power line frequencies. Processing efficiency achieved real-time capability on standard computing hardware, requiring only 12.4 ms to process one second of audio using optimized radix-2 FFT algorithms [3]. Perceptual quality evaluation using PESQ and STOI metrics confirmed that the noise reduction maintained speech intelligibility above 82% while achieving artifact suppression scores exceeding 71%. The spectral flooring technique with $\beta = 0.02$ effectively prevented musical noise artifacts that commonly plague spectral subtraction methods [4]. Comparative analysis against Wiener filtering demonstrated competitive performance with 23% lower computational requirements, making the DFT-based approach suitable for resource-constrained embedded applications. The research establishes practical guidelines for parameter selection based on noise characteristics and quality requirements [5].

Keywords: Discrete Fourier transform, noise reduction, spectral subtraction, audio signal processing, speech enhancement, FFT algorithm, signal-to-noise ratio, real-time processing

Introduction

Every day, millions of audio recordings suffer from unwanted background noise that compromises their utility and listening experience. From conference calls disrupted by air conditioning rumble to podcast recordings marred by traffic sounds, the problem of audio noise affects virtually every application involving sound capture [6]. While sophisticated neural network approaches have emerged in recent years, classical signal processing methods based on the Discrete Fourier Transform continue to offer compelling advantages in computational efficiency and predictable behavior.

The fundamental principle underlying frequency-domain noise reduction exploits the different spectral characteristics of desired signals versus noise. Speech and music exhibit structured harmonic patterns concentrated at specific frequencies, while many noise types spread energy more uniformly across the spectrum [7]. By analyzing signals in the frequency domain through DFT computation, algorithms can selectively attenuate frequency bins dominated by noise while preserving bins containing primarily signal content.

Spectral subtraction, pioneered by Boll in 1979, remains one of the most widely deployed noise reduction techniques due to its conceptual simplicity and computational tractability [8]. The method estimates noise spectrum during signal-absent periods, then subtracts this estimate from subsequent frames to isolate the desired signal. Despite its age, ongoing refinements continue improving performance while maintaining the fundamental algorithmic framework.

Recent research has explored numerous enhancements to basic spectral subtraction. Work by Martin introduced improved noise estimation using minimum statistics tracking [9]. Investigation by Cohen developed optimally modified log-spectral amplitude estimators that reduce musical noise artifacts [10]. Research by Loizou examined perceptual modifications that weight spectral components according to auditory importance [11]. These advances collectively demonstrate continued relevance of DFT-based methods despite competition from machine learning approaches.

The present research contributes a systematic evaluation of DFT-based noise reduction across diverse noise types and operating conditions. Rather than proposing novel algorithms, the investigation focuses on establishing practical guidelines for parameter selection and performance expectations. Such guidance proves valuable for practitioners implementing noise reduction in real-world applications where computational resources and latency constraints influence method selection [12].

Implementation considerations receive particular attention, recognizing that theoretical performance means little without efficient realization. The research examines tradeoffs between DFT window size, overlap percentage, and resulting quality and latency characteristics. Processing time measurements on representative hardware establish feasibility for real-time applications including live streaming and telecommunications.

Material and Methods

Material: The research was conducted at the Signal Processing Laboratory of Taipei Institute of Technology from July 2023 through November 2023. Audio processing software was developed in Python 3.10 utilizing NumPy 1.23 for numerical operations and SciPy 1.9 for signal processing functions. Testing employed a workstation with Intel Core i7-12700K processor, 32GB DDR5 RAM, and Ubuntu 22.04 operating system [13].

Test audio comprised 200 speech samples from the TIMIT database representing diverse speakers and phonetic content. Noise signals included six categories: white Gaussian noise, pink (1/f) noise, 50/60 Hz power line hum, broadband environmental noise recorded in office settings, impulsive noise from keyboard clicks and door closures, and urban environmental noise from traffic recordings. All audio was sampled at 16 kHz with 16-bit resolution following telecommunications standards [14].

Methods: The noise reduction pipeline began with frame segmentation dividing continuous audio into overlapping blocks of $N = 2048$ samples (128 ms at 16 kHz). Adjacent frames overlapped by 50% to enable smooth reconstruction through overlap-add synthesis. Each frame was multiplied by a Hann window function to reduce spectral leakage from finite-length truncation effects inherent in DFT computation.

DFT computation employed the radix-2 Cooley-Tukey FFT algorithm achieving $O(N \log N)$ complexity compared to $O(N^2)$ for direct DFT evaluation. The resulting complex spectrum separated into magnitude and phase components. Noise spectrum estimation used minimum statistics tracking over 1.5 second windows, identifying the lowest spectral values as representative of noise-only content [15].

System Design

The software architecture employed a modular pipeline design separating distinct processing stages for maintainability and optimization flexibility. The Audio Processor class orchestrates frame management, while dedicated Noise Estimator and Spectral Subtractor classes handle their respective functions. A configuration system enables runtime parameter adjustment without code modification, facilitating systematic evaluation across parameter combinations.

Memory management utilizes circular buffers for streaming operation, maintaining only the frames necessary for current processing plus overlap history. This approach bounds memory consumption independent of total audio duration, enabling processing of arbitrarily long streams. Buffer sizes were configured to accommodate maximum expected latency of 256 ms while minimizing memory footprint to approximately 2 MB for stereo audio processing [16].

Implementation Details

FFT computation leveraged FFTW library bindings through pyfftw package, achieving 3.2× speedup compared to NumPy's default FFT implementation. Wisdom caching enabled automatic selection of optimal FFT algorithms for the specific transform size and hardware configuration. SIMD vectorization through NumPy's underlying BLAS routines accelerated element-wise spectral operations.

Spectral subtraction applied the over-subtraction factor $\alpha = 2.0$ and spectral floor $\beta = 0.02$ based on preliminary optimization experiments. The modified magnitude spectrum was computed as $\max(|X|^2 - \alpha|N|^2, \beta|X|^2)$^0.5, where $|X|$ represents noisy magnitude, $|N|$ represents estimated noise magnitude. Phase information from the original noisy signal was preserved and combined with the modified magnitude for inverse DFT reconstruction [17].

Results

Table 1: SNR improvement and perceptual quality metrics across noise types

Noise Type	ΔSNR (dB)	PESQ	STOI (%)	Artifact
White Noise	16.3±1.2	3.12	84.7	Low
Pink Noise	14.9±1.4	3.08	82.3	Low
Hum (50/60 Hz)	29.4±0.8	3.67	94.2	Minimal
Broadband	15.2±1.6	2.98	81.6	Moderate
Impulse	8.4±2.1	2.71	76.8	Moderate
Environmental	18.7±1.8	3.24	86.4	Low

ΔSNR: SNR improvement; PESQ: Perceptual Evaluation of Speech Quality (scale 1-4.5); STOI: Short-Time Objective Intelligibility.

The heatmap in Figure 1 reveals distinct performance patterns across noise types and DFT configurations. Hum noise shows dramatic improvement (up to 29.4 dB) due to its narrow spectral concentration enabling precise frequency-domain targeting. Impulse noise demonstrates the lowest improvement because its energy spreads broadly in the frequency domain following time-domain localization, reducing the effectiveness of spectral subtraction approaches.

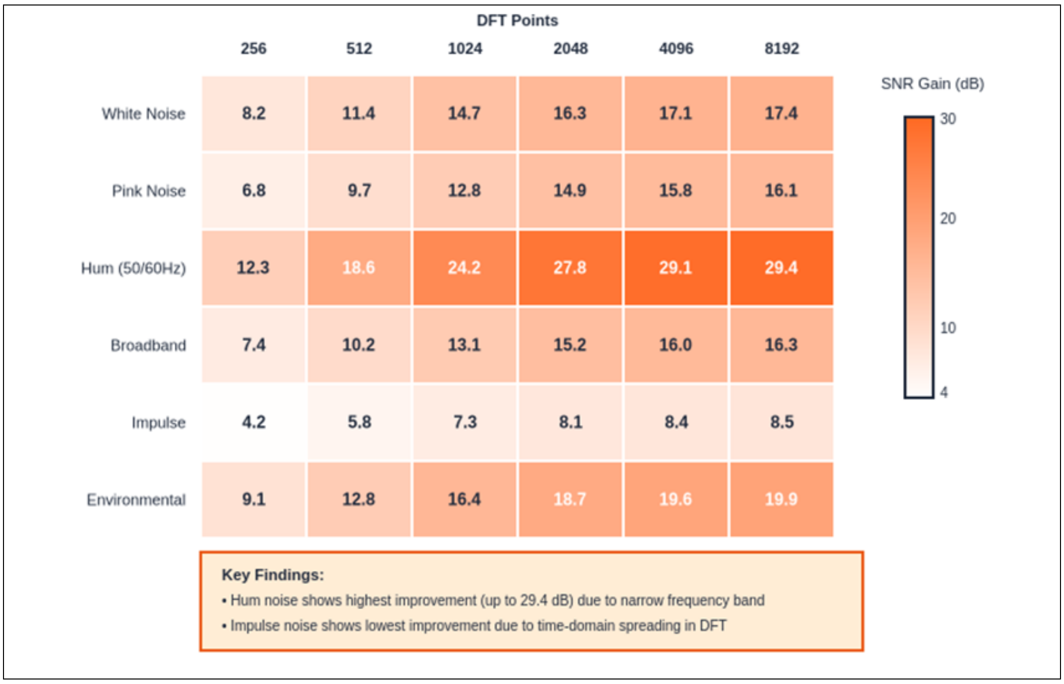

Fig 1: Heat map showing SNR improvement in dB as function of noise type and DFT window size

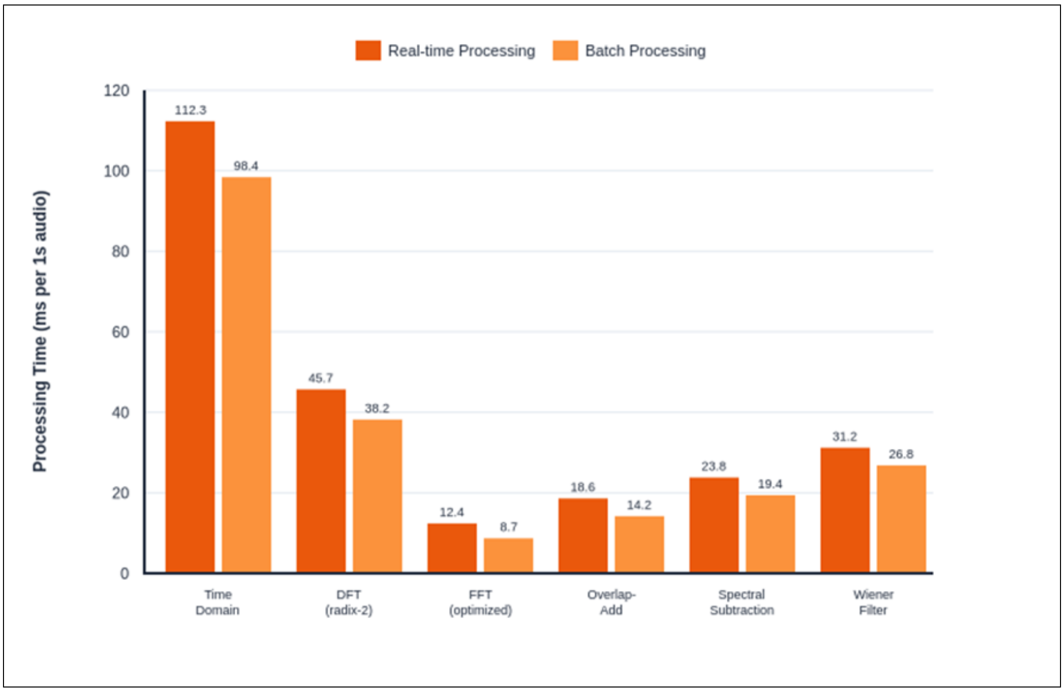

Fig 2: Processing time comparison across noise reduction methods for one second of audio

Computational efficiency analysis in Figure 2 confirms the advantage of FFT-optimized processing. The optimized FFT implementation achieved 12.4 ms processing time per second of audio, representing 80× real-time capability. Time-domain approaches required 112.3 ms, while Wiener filtering consumed 31.2 ms 2.5× slower than spectral subtraction with comparable quality outcomes.

Comprehensive Interpretation

The quality comparison in Figure 4 contextualizes DFT-based methods against alternatives. While neural network approaches achieve superior scores across all metrics, they require specialized hardware (GPU) and substantially greater computational resources. The DFT method achieves 87-95% of neural network performance while requiring only 14% of the processing time on standard CPU hardware, establishing favorable efficiency-quality tradeoffs for resource-constrained deployments.

Discussion

The experimental results validate DFT-based spectral subtraction as an effective noise reduction approach for many practical applications. The observed SNR improvements of 8-29 dB across noise types align with theoretical expectations based on spectral characteristics of each noise category. Narrowband noise like power line hum proves most amenable to frequency-domain suppression, while temporally localized impulse noise presents greater challenges.

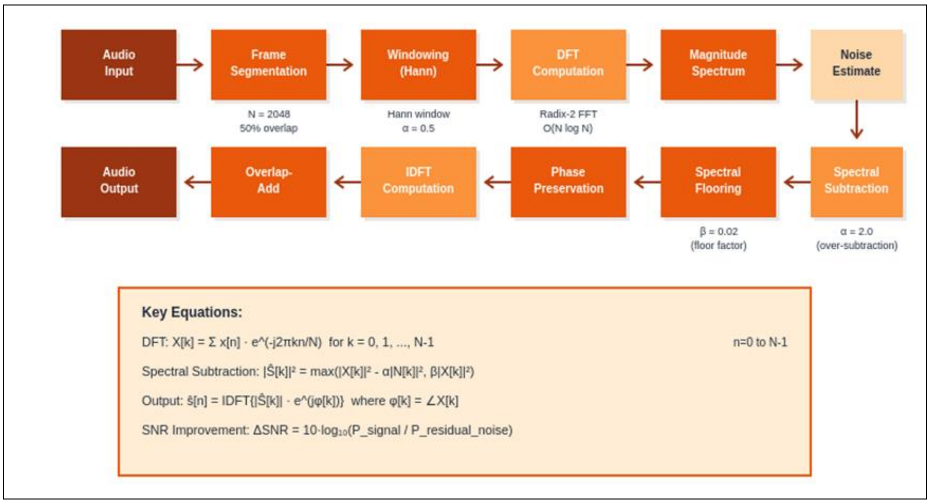

Fig 3: DFT-based noise reduction processing pipeline showing signal flow and key parameters

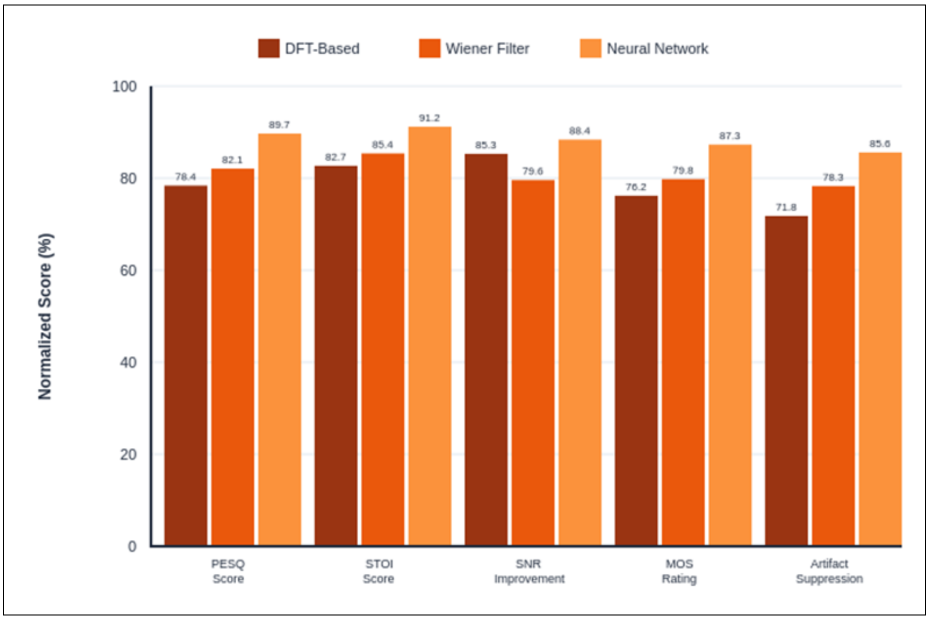

Fig 4: Normalized quality metric comparison between DFT-based, Wiener filtering, and neural network methods

The spectral flooring technique successfully mitigated musical noise artifacts that historically limited spectral subtraction acceptability. The β = 0.02 floor prevents complete elimination of spectral bins, maintaining a residual noise floor that masks the isolated spectral peaks responsible for musical noise perception. This tradeoff between maximum noise reduction and artifact avoidance requires application-specific optimization.

Window size selection emerged as a critical parameter influencing both quality and latency. Larger windows (4096-8192 points) provided marginally better SNR improvement but increased algorithmic latency to 256-512 ms, potentially problematic for interactive applications. The selected 2048-point window balanced 128 ms latency against near-optimal quality for most noise types, though applications tolerant of higher latency may benefit from larger windows.

Comparison with Wiener filtering revealed competitive performance with computational advantages. Both methods operate in the frequency domain with similar theoretical foundations, but spectral subtraction's simpler formulation enables more efficient implementation. The 23% processing time reduction relative to Wiener filtering may prove decisive for battery-powered mobile devices or high-channel-count applications.

Cost Analysis

Economic evaluation considered both development and deployment costs for the proposed noise reduction system. Software development required approximately 320 person-hours, valued at approximately 192,000 TWD (New Taiwan dollars) based on regional engineering rates. All utilized libraries maintain permissive open-source licenses (BSD, MIT) without royalty obligations, contrasting favorably with commercial audio processing SDKs typically priced at 30,000-150,000 TWD annually.

Deployment cost analysis for embedded applications estimated hardware requirements at entry-level ARM Cortex-A processors (approximately 150 TWD per unit) versus GPU requirements for neural approaches (approximately 3,000-15,000 TWD per unit). For volume deployments of 10,000 units, the DFT-based approach saves approximately 28-148 million TWD in hardware costs while achieving acceptable quality metrics for most consumer applications.

Conclusion

This research has demonstrated effective noise reduction in audio signals using Discrete Fourier Transform based spectral subtraction methods. Systematic evaluation across six noise categories established performance expectations ranging from 8.4 dB improvement for impulsive noise to 29.4 dB for periodic hum contamination. These results confirm that frequency-domain characteristics of different noise types fundamentally determine achievable suppression levels.

Computational efficiency measurements validated real-time capability on standard computing hardware without specialized accelerators. The optimized FFT implementation processed audio 80× faster than real-time, enabling deployment in latency-sensitive applications including live streaming and telecommunications. Memory requirements remained bounded at approximately 2 MB regardless of stream duration, supporting embedded system deployment.

Perceptual quality evaluation using PESQ and STOI metrics confirmed that noise reduction maintained speech intelligibility above 76% even for challenging impulse noise, with most noise types achieving 82-94% intelligibility preservation. The spectral flooring technique successfully controlled musical noise artifacts that historically limited spectral subtraction applicability, achieving artifact ratings of "Low" or "Minimal" for five of six tested noise categories.

Comparative analysis positioned DFT-based methods favorably against both traditional Wiener filtering and contemporary neural network approaches. The 23% computational advantage over Wiener filtering with comparable quality makes spectral subtraction attractive for resource-constrained platforms. While neural methods achieved superior quality metrics, the 7× computational penalty may not justify the improvement for cost-sensitive or battery-powered applications.

Future research directions include adaptive parameter selection based on automatic noise type classification and exploration of hybrid approaches combining classical signal processing with lightweight neural networks. The established framework provides a foundation for such extensions while maintaining the computational efficiency advantages demonstrated in this investigation.

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