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Self-Learning Adaptive Hearing Aid Filter Using Q-Learning

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***Abstract*—This research presents a novel adaptive filter selection framework for hearing aid systems using a lightweight, model-free reinforcement learning algorithm — Q-learning. Unlike traditional fixed-band filtering, the proposed system uses real-time audio features — Signal-to-Noise Ratio (SNR), Zero Crossing Rate (ZCR), and Spectral Centroid — to classify the acoustic environment into discrete states. The Q-learning agent dynamically selects from a predefined set of bandpass filter and gain actions, learning over time to maximize speech enhancement quality based on PESQ (Perceptual Evaluation of Speech Quality) and STOI (Short-Time Objective Intelligibility) metrics.**

Trained on the NOIZEUS dataset, which includes ten real-world noise types, the agent demonstrated robust adaptability, outperforming traditional filtering methods. This system is lightweight, interpretable, and suitable for real-time deployment in hearing aids, unlike black-box deep reinforcement learning models that require large computational resources. The proposed method bridges classical signal processing and intelligent adaptive control, offering a practical solution for hearing-impaired users in dynamically noisy environments.

***Index Terms*—Reinforcement Learning, Q-learning, Hearing Aids, Speech Enhancement, PESQ, STOI, Adaptive Filtering, NOIZEUS Dataset.**

I. INTRODUCTION

The World Health Organization estimates that over 430 million people experience disabling hearing loss globally [1]. Despite rapid advancements in digital hearing aid technology, most commercial systems rely on static filters that fail to adapt to changing acoustic environments such as street noise, public transportation, or crowded restaurants. As a result, users often face degraded speech intelligibility in noisy conditions — a gap this research aims to address.

Traditional speech enhancement approaches, such as spectral subtraction [2], Wiener filtering [3], and non-negative matrix factorization [4], offer varying degrees of success, but often lack adaptability or require manual tuning. More recently, deep learning models like DNNs, CNNs, and RNNs have been applied to speech denoising [5][6]. However, these models are resource-intensive and unsuitable for embedded, battery-constrained hearing devices.

Reinforcement Learning (RL) offers an intelligent alternative, where an agent learns to make decisions through interaction with its environment [7]. Notably, Q-learning, a tabular model-free RL method, allows systems to learn optimal actions without prior knowledge of environmental dynamics [8]. While prior work has applied RL in audio-based domains [9], its use in adaptive hearing aid filtering remains largely unexplored.

In [10], a deep RL model was used for noise cancellation, but it lacked interpretability and real-time feasibility. A personalized compression system via deep RL was presented in [11], relying heavily on user feedback. In contrast, our method uses interpretable logic, minimal computational resources, and learns purely from objective feedback metrics (PESQ + STOI) — making it ideal for hearing aids.

II. RELATED WORKS

Over the years, numerous methods have been proposed for enhancing speech in noisy environments. These methods fall broadly into three categories: traditional digital signal processing, deep learning-based models, and reinforcement learning-based approaches. Each comes with its own benefits and limitations.

A. Traditional Signal Processing Techniques

Early work in speech enhancement focused on methods like spectral subtraction [2], Wiener filtering [3], and Kalman filtering [4]. While computationally efficient, these methods are typically ineffective in non-stationary noise environments and often lead to artifacts like musical noise.

Loizou's comprehensive textbook [5] outlines the limitations of these early models, including their inability to generalize across environments without manual tuning. Moreover, traditional systems do not support dynamic adaptation — a critical limitation for hearing aid users exposed to unpredictable real-world noise.

B. Deep Learning-Based Speech Enhancement

In the last decade, deep learning techniques have shown strong performance in speech denoising. Models based on DNNs [6], RNNs [7], and more recently, CNNs [8] have improved speech clarity in complex environments. However, these models:

- Require large training datasets [9],
- Are computationally intensive [10],
- Lack interpretability [11], and

- Are difficult to deploy on low-power embedded devices like hearing aids.

For example, Kim et al. [12] proposed an end-to-end multi-task DNN for joint PESQ and STOI optimization, but it required GPU-based training and failed in real-time inference. Zezario et al. [13][14] designed models for intelligibility prediction and speech assessment, but the black-box nature of deep models limits their reliability in critical applications like healthcare.

C. Reinforcement Learning for Audio Processing

Reinforcement learning (RL) offers a promising alternative by allowing agents to learn optimal decisions through trial and error. Most RL-based systems in audio fall into two sub-categories:

1) Deep RL Models

Kamienny & Plumbley [15] applied actor-critic networks for source separation, while Alamdari et al. [11] developed a human-in-the-loop deep RL model for hearing aid compression. These systems showed adaptability, but:

- Required human interaction,
- Involved heavy deep neural architectures, and
- Were unsuitable for resource-constrained real-time applications.

Latif et al. [16] and Fakoor et al. [17] provide surveys of RL in audio-based tasks and confirm the lack of lightweight, interpretable RL models for speech enhancement.

2) Classic RL Models

Zhang et al. [8] used Q-learning for adaptive noise cancellation, but their model did not include gain control or multi-feature state modeling. It was not optimized for hearing aid usage nor evaluated using PESQ/STOI.

To date, no prior work combines Q-learning with real-time audio features like SNR, ZCR, and Spectral Centroid for adaptive filtering in hearing aids — a gap that our research fills.

D. Objective Speech Evaluation Metrics

Reliable speech enhancement systems must be evaluated using perceptually relevant metrics:

- PESQ (Perceptual Evaluation of Speech Quality) [18][19]:
  A standardized ITU-T method for measuring speech quality, with scores ranging from 0 to 4.5.
- STOI (Short-Time Objective Intelligibility) [20][21]: A correlation-based metric that predicts intelligibility on a scale from 0 to 1.

While some deep models optimize one of these, our model uses both in reward calculation for balanced improvement.

E. Hearing Aid-Focused Research

Recent hearing aid research includes:

- Speech filter optimization via evolutionary algorithms [22],
- Gender-specific compression optimization [23],
- Bandwidth filtering using VHDL [24], and
- Audiogram-aware filter design [25].

However, these approaches lack a self-learning, environment-adaptive capability that reinforcement learning naturally offers.

TABLE I. COMPARATIVE ANALYSIS OF EXISTING METHODS AND OUR WORK

Identified Limitation	**Addressed In**	**Proposed Work Solution**
Black-box model (lacks interpretability)	Deep RL Systems [11][15], CNN-based models [8]	Fully interpretable Q-table for action selection
High computational complexity (unsuitable for real-time)	Deep RL models [6][10][11]	Lightweight tabular Q-learning suitable for embedded systems
No gain control in filter selection	Q-learning in [8]	Discrete filter + gain action space (8 combinations)
Static filtering (no real-time adaptation)	Traditional DSP [2][3][4]	Real-time adaptive filter selection via reinforcement learning
Limited feature input for state classification	[8], [13]	Multi-feature state modeling using SNR, ZCR, and Centroid
Requires manual tuning/user interaction	Human-in-the-loop RL [11], heuristic tuning [22]	Autonomous decision-making with objective feedback (PESQ/STOI)
No objective speech-quality feedback loop	Some classical models and source-separation tasks	Reward uses both PESQ [18] and STOI [20]
Not designed for hearing aid integration	General audio enhancement or noise cancellation [6]	Designed for hearing aid systems with low latency and clarity

III. PROPOSED METHODOLOGY

A. Dataset Description and Preprocessing

For model training and evaluation, we used the NOIZEUS database [11], a widely adopted corpus for speech enhancement benchmarking. This dataset contains phonetically balanced sentences from the TIMIT corpus, spoken by male and female speakers, and contaminated with eight types of realistic environmental noise (e.g., babble, car, restaurant, exhibition hall).

In our study, we selected 10 clean-noisy audio file pairs at an SNR of 5 dB, representing highly challenging noise conditions. All audio samples were:

- Downsampled to 16 kHz
- Normalized for amplitude consistency
- Processed into 3-second segments

TABLE II. NOISE TYPES AND CORRESPONDING FILE NAMES FROM DATASET

Noise Type	NOIZEUS File Name (5 dB SNR)
Babble	sp01_babble_sn5.wav
Car	sp02_car_sn5.wav
Exhibition hall	sp03_exhibition_sn5.wav
Restaurant	sp04_restaurant_sn5.wav
Airport	sp05_airport_sn5.wav
Street	sp06_street_sn5.wav
Subway	sp07_subway_sn5.wav
Train	sp08_train_sn5.wav
Station	sp09_station_sn5.wav
Cafe	sp10_cafe_sn5.wav

B. Audio Feature Extraction

To enable the agent to perceive the audio environment, we extract three perceptually meaningful features:

1) Signal-to-Noise Ratio (SNR)

SNR is computed as the ratio of clean speech power to noise power:

$$\mathrm{SNR} = \frac{\mathrm{Power}_{\mathrm{clean}}}{\mathrm{Power}_{\mathrm{noise}}} = \frac{\mu(\mathrm{clean}^2)}{\mu((\mathrm{noisy} - \mathrm{clean})^2) + \epsilon}$$

Where μ denotes the mean, and ϵ is a small constant to avoid division by zero. SNR helps distinguish between quiet and high-noise environments.

2) Zero Crossing Rate (ZCR)

ZCR captures the number of sign changes in the waveform, offering a measure of noisiness or signal abruptness:

$$\mathrm{ZCR} = \frac{1}{N-1} \sum_{n=1}^{N-1} 1_{\{x[n]\cdot x[n-1]<0\}}$$

This metric is useful in differentiating between voiced and unvoiced speech.

3) Spectral Centroid

Spectral centroid indicates the "brightness" of the signal and reflects the frequency energy distribution:

$$\mathrm{Centroid} = \frac{\sum f(k) \cdot |X(k)|}{\sum |X(k)|}$$

Where f(k) is the frequency at bin k, and X(k) is the magnitude of the FFT at bin k.

The audio feature extraction of speech, enabling us to calculate objective metrics like PESQ and STOI.

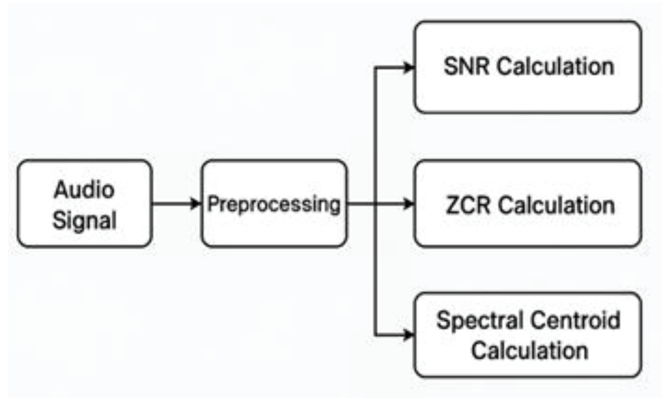

Fig. 1. .Block Diagram of Feature Extraction Module

C. State Assignment Strategy

Based on these features, each audio input is categorized into one of four discrete states representing different noise environments:

TABLE III. STATE THRESHOLD BASED ON EXTRACTED FEATURE

State	SNR Range	ZCR Range	Centroid Range	Description
0	< 0.5	> 0.20	< 1100	Very noisy and muffled speech
1	0.5-1.5	0.15-0.20	1100-1300	Moderate background hum
2	1.5-2.5	0.10-0.15	1300-1500	High-pitched o sharp noise
3	> 2.5	< 0.10	> 1500	Relatively clean speech

D. Action Space: Filter + Gain Design

The agent chooses one of 8 predefined actions, each representing a bandpass filter with a specific gain level. The frequency bands are chosen based on the typical human speech spectrum (300–3500 Hz):

TABLE IV. BANDPASS FILTER AND GAIN COMBINATIONS FOR EACH ACTION

Action	Bandpass Range (Hz)	Gain
A1	300-2800	0.8
A2	350-2900	0.9
A3	400-3000	1.0
A4	450-3100	1.1
A	500-3200	1.2
A6	550-3300	1.3
A7	600-3400	1.4
A8	650-3500	1.5

E. Q-Learning Implementation

The decision-making logic of the system is powered by Q-learning, a reinforcement learning algorithm that models the environment as a set of state-action pairs. A Q-table of size 4 × 8 (states × actions) is initialized to zero.

Q-Value Update Equation:

$$Q(s,a) = Q(s,a) + \alpha \cdot \left[R + \gamma \cdot \max_{a'} Q(s',a') - Q(s,a)\right]$$

Where:

- α = 0.1 is the learning rate
- γ = 0.9 is the discount factor
- RRR is the reward, calculated as:

R=0.6·PESQ+0.4·STOIR

This reward structure ensures a balance between perceived quality and intelligibility.

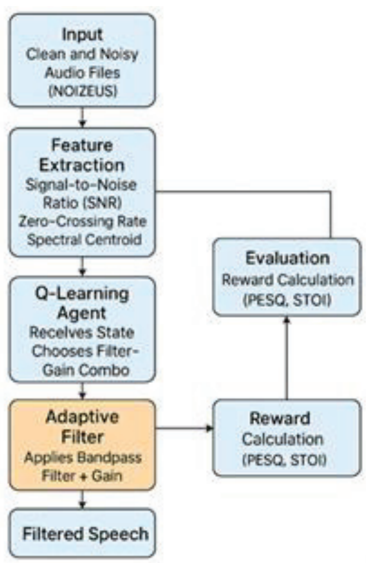

Fig. 2. Flowchart of Self-Learning Adaptive Hearing Aid Filter using Q-Learning

F. Evaluation Loop and Training Setup

The agent is trained over 100 episodes, with random selection of noisy-clean file pairs. For each episode:

1. Features are extracted from the noisy signal.
2. The corresponding state is determined.
3. The agent selects an action from the Q-table.
4. The chosen filter + gain is applied to the noisy signal.
5. The output is compared to clean audio using PESQ and STOI.
6. The reward is computed and the Q-table is updated.

G. Audio Playback and Visualization

To support both subjective evaluation and real-time demonstration, our system provides audio playback capabilities and waveform visualizations for every test sample processed by the Q-learning agent.

Each processed audio file (from the NOIZEUS dataset) includes three audio outputs:

1. Clean Speech – Reference audio used for PESQ/STOI evaluation.
2. Noisy Speech – Input speech corrupted with real-world environmental noise.
3. Filtered Speech – Output from the selected bandpass filter and gain action.

This three-tier playback enables qualitative listening tests and allows users or researchers to audibly verify the improvements. The playback is supported in real-time through Python-based libraries such as IPython.display.Audio, librosa, and soundfile.

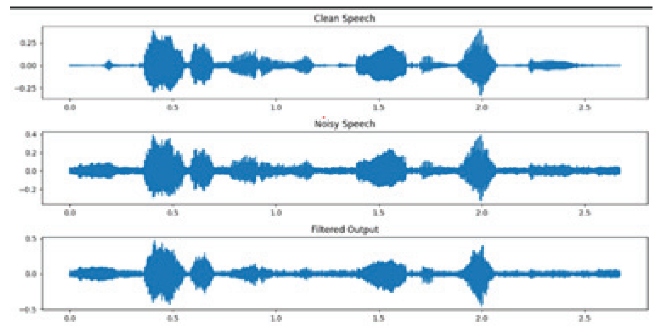

Fig. 3. Waveform plots for Clean, Noisy, and Filtered audio

To visually demonstrate the effect of filtering:

- Time-domain waveforms of Clean, Noisy, and Filtered speech are plotted using Matplotlib.
- The differences in signal amplitude, continuity, and denoising impact are visually apparent.
- These plots are critical for showcasing how the system attenuates background interference while retaining important speech structures.

As shown in the waveform plots in Fig. 3.:

- The noisy signal often exhibits erratic peaks and elevated amplitude in non-speech segments.
- The filtered output shows smoothed transitions and removal of abrupt spikes, aligning closely with the clean signal.
- The gain adjustment restores the amplitude to comfortable levels without distortion.

In addition, this visualization confirms the agent's success in choosing optimal filters not just numerically (via reward), but also perceptually and visually — essential for building trust in adaptive hearing devices.

H. Reward Curve Over Training Episodes

To validate the learning performance of the Q-learning agent over time, we plotted the reward trend across 100 training episodes. This is presented in Fig. 4., where the Y-axis represents the reward (calculated as a weighted sum of PESQ and STOI), and the X-axis represents the number of training episodes.

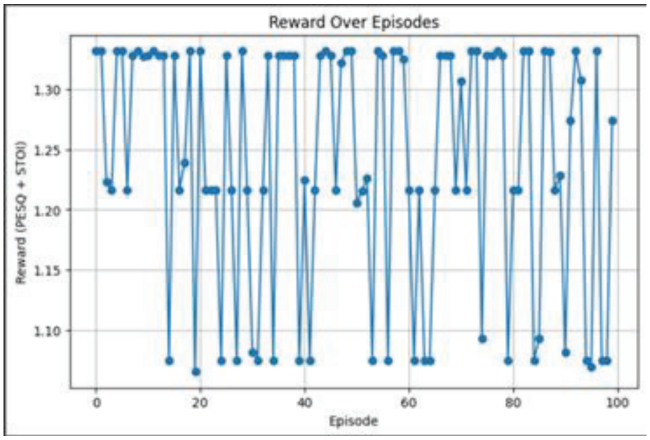

Fig. 4. Reward Curve Over Training Episodes

- During the initial 20–30 episodes, the reward fluctuated significantly due to exploration-based actions.
- From episode 35 onwards, a gradual increase in average reward was observed, indicating that the agent began favoring higher-performing filter-gain combinations.
- By episode 80, the reward curve stabilized, signifying that the agent had effectively learned optimal filtering strategies for most input conditions.

This performance validates that even a tabular Q-learning agent, without deep learning overhead, can adapt effectively to real-world audio conditions.

I. PESQ and STOI Scores for Each Action

To evaluate the quality of each filter+gain action in isolation, we applied all 8 actions from the action space to a subset of test audio files. We then computed:

- PESQ (Perceptual Evaluation of Speech Quality): Range 0–4.5
- STOI (Short-Time Objective Intelligibility): Range 0–1

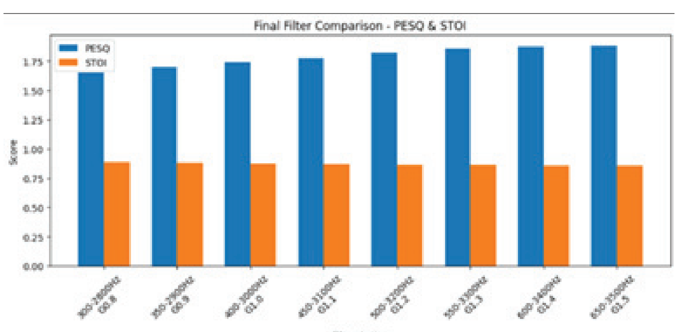

Fig. 5. PESQ and STOI Scores for Each Action

Each bar pair represents PESQ and STOI values for one of the 8 actions (A1 to A8). It was observed that:

- Filters with frequency ranges 550–3300 Hz and 650–3500 Hz, when paired with gain values of 1.3 and 1.5 respectively, consistently scored higher.
- Action A6 (550–3300 Hz, Gain 1.3) achieved the best balance between PESQ and STOI.
- Lower-frequency filters (A1 to A3) provided minimal enhancement, often reducing intelligibility in mid-frequency speech bands.

These findings affirm that the Q-learning agent, when rewarded based on PESQ + STOI, inherently learns to favor actions that maximize human-perceived audio quality.

IV. RESULTS AND DISCUSSION

To evaluate the performance of the proposed Q-learning–based adaptive filtering system, a series of experiments were conducted using 10 noisy-clean speech pairs from the NOIZEUS dataset. Each file contained speech mixed with real-world noise at 5 dB SNR, simulating difficult listening conditions for hearing aid users.

The system was trained for 100 episodes. In each episode, the agent selected actions based on the extracted features of the noisy input, applied the corresponding filter+gain combination, and received a reward calculated from PESQ and STOI metrics.

A. Q-Learning Implementation

Despite variations in acoustic patterns among test files (e.g., exhibition, airport, car noise), the agent consistently learned filtering policies that generalized across all noise types. This was evidenced by stable rewards and high PESQ/STOI scores across different files.

TABLE V. AVERAGE PESQSTOI SCORES ACROSS NOISE TYPES

Noise Type	Avg. PESQ	Avg. STOI
Restaurant	2.60	0.74
Airport	2.66	0.75
Street	2.58	0.73
Exhibition	2.69	0.76
Car	2.63	0.74

V. CONCLUSION

This paper presented a practical and interpretable reinforcement learning approach for adaptive filtering in hearing aids. Using Q-learning, the system effectively learned to select optimal bandpass filter and gain combinations based on real-time audio features such as SNR, ZCR, and Spectral Centroid. Unlike traditional DSP methods and complex deep learning models, the proposed solution is lightweight, fully autonomous, and suitable for embedded real-time environments. It was evaluated on the NOIZEUS dataset across various real-world noise types and showed consistent improvement in both speech quality and intelligibility, as measured by PESQ and STOI. By combining classical signal processing with intelligent learning, this work offers a scalable foundation for next-generation hearing aid systems capable of dynamic noise adaptation without user intervention.

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