SRINIVAS UNIVERSITY
INSTITUTE OF ENGINEERING & TECHNOLOGY

(SUBJECT: ARTIFICIAL NEURAL NETWORKS)

(SUBJECT CODE: 24SBT113)

AN GROUP TASK REPORT ON

"ANN-Based Noise Cancellation"

Submitted in the partial fulfillment of the requirements for the First semester

BACHELOR OF TECHNOLOGY
IN
ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

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2025-26

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CERTIFICATE

This is to certify that, **SREERANJINI P(01SU24AI102),VARCHA C(01SU24AI114),CHANDRIKA(01SU25AI702)**has satisfactorily completed the assessment (Group Task) in **ARTIFICIAL NEURAL NETWORKS (24SBT113)** prescribed by the Srinivas University for the 4th semester B. Tech course during the year **2025-26**.

MARKS AWARDED

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Date: 23.02.2026

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Introduction

In modern communication and signal processing systems, noise is one of the most significant factors that degrade signal quality and system performance. Noise refers to any unwanted disturbance that interferes with the original signal during transmission, recording, or processing. It can originate from various sources such as environmental interference, electronic components, electromagnetic radiation, or background sounds. In applications like speech communication, biomedical signal processing, audio engineering, and wireless transmission, the presence of noise can severely reduce intelligibility, accuracy, and reliability. Therefore, effective noise cancellation techniques are essential for improving signal clarity and overall system efficiency.

Traditional noise cancellation methods, such as linear filtering techniques (e.g., adaptive filters, Wiener filters, and Kalman filters), have been widely used to reduce noise. While these methods perform well in controlled and linear environments, they often struggle in real-world situations where noise is non-linear, non-stationary, and unpredictable. As a result, researchers have explored intelligent and adaptive approaches capable of handling complex noise patterns. Artificial Neural Networks (ANNs) have emerged as a powerful solution in this domain.

Artificial Neural Networks are computational models inspired by the structure and functioning of the human brain. They consist of interconnected processing units (neurons) organized into layers and capable of learning patterns from data. Through training algorithms such as Backpropagation, ANNs can adjust their internal parameters to minimize error between predicted and desired outputs. This learning capability allows them to model complex and non-linear relationships between noisy and clean signals.

ANN-based noise cancellation systems work by training the network with examples of noisy signals and their corresponding clean versions. Over time, the network learns to distinguish useful signal components from unwanted noise. Once trained, the ANN can effectively suppress noise in new, unseen signals. Unlike conventional filtering techniques, ANN-based methods are adaptive, data- computational power and data availability continue to grow, ANN-based approaches are becoming increasingly important in developing intelligent, efficient, and real-time noise reduction systems.driven, and capable of handling dynamic noise environments.

With advancements in deep learning architectures such as feedforward neural networks, recurrent neural networks, and convolutional neural networks, ANN-based noise cancellation has achieved remarkable performance in applications like speech enhancement, medical signal denoising, and audio restoration. As

Objectives

The main objectives of this project are:

1. To understand the concept of noise cancellation Gain a clear understanding of how unwanted noise affects signals and how noise reduction techniques improve signal quality.
2. To model an ANN architecture for noise reduction Design a conceptual neural network structure that can process noisy inputs and generate a cleaner output signal.
3. To identify suitable neuron types Analyze the types of neurons and activation functions that are most appropriate for handling signal processing tasks.
4. To select an appropriate learning law Determine the learning mechanism that allows the network to adjust its weights and minimize the difference between noisy and clean signals.
5. To explain the working process of ANN in this application Describe step-by-step how the neural network receives input, processes data, learns from errors, and produces the final noise-reduced signal.

Overview of Noise Cancellation

Noise cancellation works by identifying unwanted components present in a signal and reducing or eliminating them to improve clarity and quality. The main objective is to preserve the useful information while minimizing the effect of background disturbances. In practical applications, noise can vary in intensity and pattern, so different techniques are used depending on the environment and system requirements. There are two primary approaches to noise cancellation: Passive Noise Cancellation This method relies on physical barriers to block external noise. Materials such as foam padding or insulated ear cushions reduce the amount of sound that reaches the ear. While simple and energy-efficient, passive methods are generally effective only for high-frequency or constant noise and cannot adapt to changing environments. Active Noise Cancellation (ANC) Active noise cancellation uses electronic processing to generate an anti-noise signal that has the same amplitude but opposite phase to the unwanted sound. When the two signals combine, they cancel each other through destructive interference, significantly reducing noise levels. This approach is more effective for low-frequency and dynamic noise. 3 ANN-based noise cancellation is considered an advanced form of active noise cancellation. Instead of using fixed filters, the neural network learns to distinguish between noise and the desired signal by analyzing data patterns. This learning capability allows the system to adapt to complex and changing noise conditions, making it more flexible and efficient than traditional methods.

ANN Structure for Noise Cancellation

The ANN model for noise cancellation typically follows a feedforward architecture, where information flows in one direction from the input layer to the output layer through one or more hidden layers. This structure is suitable because it allows the network to process signal features step by step and gradually refine the representation of the noisy input.

1 Input Layer

The input layer is responsible for receiving the raw data that the network will process. In a noise cancellation system, the inputs generally include: • Noisy signal samples — These are the primary audio or signal inputs that contain both the desired information and unwanted noise. • Reference noise signal (optional) — In some systems, a separate microphone or sensor captures only the background noise, which helps the network learn noise patterns more accurately. Each neuron in the input layer represents a specific feature of the signal, such as amplitude values, time-domain samples, or frequency components obtained through signal transformation techniques. The input layer does not perform complex computations; instead, it passes the processed features to the hidden layers for further analysis.

2 Hidden Layers

The hidden layers play a crucial role in the noise cancellation process by analyzing the input data and learning the relationship between noisy and clean signals. These layers perform most of the computational work in the network. By using multiple hidden layers, the ANN can capture complex and non-linear characteristics of the signal, enabling it to distinguish subtle noise patterns from the useful information. The main functions performed by the hidden layers include: • Feature extraction — Identifying important characteristics of the signal, such as patterns in time or frequency domains. • Noise pattern detection — Recognizing repetitive or irregular noise components present in the input. • Signal reconstruction — Transforming the processed features into a representation that is closer to the original clean signal. 4 Through these operations, the hidden layers gradually refine the input data and prepare it for accurate output generation.

3 Output Layer

The output layer generates the final result of the network, which is the estimated clean signal after noise has been reduced. Typically, this layer uses linear neurons so that it can produce continuous signal values rather than discrete classifications. The primary objective of the network during training is to minimize the difference between the predicted output and the actual clean signal. This difference is measured using an error or loss function, and the network adjusts its weights accordingly to improve performance. As training progresses, the output becomes increasingly closer to the original signal, indicating successful noise suppression and effective learning by the ANN.

Types of Neurons Used

1 Linear Neurons Linear neurons are typically used in the output layer because the task of noise cancellation involves reconstructing a continuous signal rather than producing discrete class labels. These neurons provide outputs that are directly proportional to their inputs, allowing the network to generate smooth and accurate signal values that closely match the original clean signal.

2 Nonlinear Neurons (ReLU / Sigmoid) Nonlinear neurons are commonly used in the hidden layers to enable the network to learn complex and non-linear relationships between noisy and clean signals. Activation functions such as ReLU or Sigmoid introduce nonlinearity, which allows the model to capture intricate noise patterns and variations that cannot be handled by linear transformations alone.

3 Adaptive Neurons Adaptive neurons adjust their weights dynamically during training based on the input data and calculated error. This adaptability helps the network respond effectively to changing noise conditions and improves its ability to generalize across different environments. As a result, the system becomes more robust and capable of handling real-world noise variations. 5

Suitable Learning Law

The most suitable learning law for noise cancellation is Error-Correction Learning, which falls under supervised learning. In this approach, the neural network is trained using pairs of input and target outputs, allowing it to learn how to transform a noisy signal into a clean one. Why Error-Correction Learning? • The network learns from examples that contain both noisy signals and their corresponding clean versions. • By comparing its predicted output with the desired output, the network identifies how far its prediction is from the actual signal. • This difference, known as the error, guides the adjustment of weights so that future predictions become more accurate. The error is calculated as: $Error = Desired\ Output - Predicted\ Output$ Based on this error, the weights are updated using gradient-based optimization techniques such as backpropagation. This process iteratively reduces the error and improves the network's ability to reconstruct clean signals. Loss Function To measure how well the network is performing, a loss function is used. For noise cancellation tasks, the Mean Squared Error (MSE) is commonly applied because it quantifies the average difference between predicted and actual signal values. 1 $MSE = \sum(y - y\ )2$ □ □ $true\ pred$ A lower MSE indicates that the predicted signal is closer to the original clean signal, showing better noise reduction performance.

Working Process of ANN Noise Cancellation

1. Noisy signal is fed into the network The input layer receives the signal that contains both the desired information and unwanted noise. These samples are converted into numerical features and passed to the next layers for processing.

2. Hidden layers analyze noise patterns The hidden layers process the input using weighted connections and activation functions to identify patterns associated with noise and useful signal components. This stage is responsible for feature extraction and separation of relevant information.

3. Output layer reconstructs clean signal After processing, the output layer generates an estimated version of the clean signal by combining the learned features and filtering out noise components.

4. Error between predicted and actual signal is computed The predicted output is compared with the target clean signal to calculate the error, which indicates how accurately the network performed the noise reduction.

5. Weights are updated to reduce error Using the error-correction learning rule and optimization techniques, the network adjusts its weights and bias values to improve performance in subsequent iterations.

6. Process repeats until noise is minimized The training process continues for multiple iterations or epochs until the error becomes sufficiently small, indicating that the network has learned to effectively suppress noise and produce a clearer signal

Real-World Applications

1. Noise-cancelling headphones Neural network algorithms help reduce background sounds such as engine noise or crowd chatter, providing a clearer and more immersive listening experience.

2. Speech enhancement systems ANN-based models improve speech clarity in voice assistants, conferencing tools, and public address systems by filtering out environmental noise.

3. Hearing aids Advanced noise reduction techniques enable hearing aids to isolate important sounds like speech while minimizing surrounding noise, improving user comfort and understanding.

4. Audio recording software Noise cancellation helps enhance the quality of recordings by removing unwanted background disturbances during editing or real-time processing.

5. Telecommunication systems In mobile and VoIP communications, neural network–based noise reduction improves call quality by suppressing interference and ensuring clearer transmission.

Conclusion

ANN-based noise cancellation has erged as an advanced and intelligent solution for improving signal quality in modern communication and signal processing systems. Unlike traditional filtering techniques that rely on predefined mathematical models and assumptions, Artificial Neural Networks (ANNs) provide a data-driven approach capable of learning complex and non-linear relationships between noisy and clean signals. This makes them highly effective in real-world environments where noise is often unpredictable, time-varying, and non-stationary.

By using supervised learning algorithms such as Backpropagation, ANN models are trained to minimize the difference between the noisy input signal and the desired clean output. Through iterative weight adjustment and error correction, the network gradually learns to identify noise patterns and suppress them while preserving essential signal information. As a result, ANN-based systems can achieve significant improvements in signal-to-noise ratio (SNR), speech intelligibility, and overall audio clarity.

The flexibility of ANN architectures—including feedforward networks, recurrent neural networks (RNNs), convolutional neural networks (CNNs), and deep neural networks (DNNs)—further enhances their effectiveness across various applications. These include speech enhancement in mobile communication, background noise reduction in voice assistants, denoising of biomedical signals such as ECG and EEG, and restoration of audio recordings.

However, ANN-based noise cancellation also presents certain challenges, such as the need for large training datasets, high computational requirements, and potential overfitting. Despite these limitations, continuous advancements in deep learning, hardware acceleration, and model optimization techniques are making ANN-based systems more efficient and practical for real-time implementation.

In conclusion, ANN-based noise cancellation represents a powerful and adaptive approach that overcomes many limitations of traditional methods. With ongoing research and technological improvements, it is expected to play an increasingly important role in future intelligent communication and signal processing systems.