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A Group Task on

"ANN-Based Noise Cancellation: Architecture, Neuron Types, and Learning Law"

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

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CERTIFICATE

This is to certify that PRADEEP (01SU24AI073), RAHUL HALASAGI (01SU24A080), RAVI MAHESH (01SU24AI082), SACHIN B KOTI (01SU24AI089) has satisfactorily completed the assessment (Group-Task – Module 1) in **"ARTIFICIAL NEURAL NETWORK "** prescribed by the Srinivas University for the 4st semester B. Tech course during the year **2025-26**.

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Abstract

Noise cancellation is an important signal processing application widely used in modern electronic devices such as headphones, telecommunication systems, hearing aids, and medical instruments. In real-world environments, signals are often corrupted by background noise, which reduces clarity and overall performance. Traditional signal processing techniques, while effective for simple and stationary noise, often struggle to handle complex, non-linear, and time-varying noise patterns.

Artificial Neural Networks (ANNs) offer a powerful and adaptive alternative by learning underlying patterns directly from data. Their ability to model complex relationships enables them to distinguish between useful signals and unwanted noise more effectively than conventional methods. This project focuses on modeling an ANN-based noise cancellation system by mapping the network architecture, identifying suitable neuron types, and selecting an appropriate learning law.

The study explains the working mechanism of the proposed model and highlights how the neural network processes noisy inputs, learns from error feedback, and reconstructs a cleaner signal. Through this analysis, the project demonstrates the effectiveness and practical relevance of ANN techniques in solving real-world noise reduction problems and improving signal quality in dynamic environments.

1. Introduction

In real-world environments, signals are often corrupted by unwanted noise, which reduces clarity and affects overall system performance. For instance, during phone calls, audio recordings, or live communication, background sounds such as traffic, wind, machinery, or crowd noise interfere with the desired signal. These disturbances make it difficult to accurately interpret or transmit information. Noise cancellation techniques aim to identify and remove these unwanted components while preserving the original signal as much as possible, thereby improving signal quality and intelligibility.

Artificial Neural Networks are particularly well suited for this task because of their ability to learn complex and non-linear relationships between noisy and clean signals. By training on sample data that contains both types of signals, an ANN can automatically recognize noise patterns and predict a cleaner output. Unlike traditional filters, neural networks can adapt to changing noise conditions and perform effectively even in dynamic environments.

This project focuses on modeling an ANN-based noise cancellation system by analyzing and identifying the following key components:

- The network architecture used to process and transform the signal
- The types of neurons responsible for feature extraction and signal reconstruction
- The learning rule employed to train the network and minimize error

2. 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.

3. 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.

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.

4. 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.

4.1 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.

4.2 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.

Through these operations, the hidden layers gradually refine the input data and prepare it for accurate output generation.

4.3 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.

5. Types of Neurons Used

5.1 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.

5.2 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.

5.3 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.

6. 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.

$$MSE = \frac{1}{n}\sum(y_{true} - y_{pred})^2$$

A lower MSE indicates that the predicted signal is closer to the original clean signal, showing better noise reduction performance.

7. 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.

8. Advantages of ANN in Noise Cancellation

- **Can learn complex noise patterns**
  Neural networks can model intricate and non-linear relationships in signals, allowing them to identify and remove complex noise that traditional filters may not handle effectively.
- **Adaptive to changing environments**
  Since the network learns from data, it can adapt to variations in noise characteristics, making it suitable for dynamic and real-world conditions.
- **Improves signal quality significantly**
  By accurately separating noise from the desired signal, ANN-based systems enhance clarity and intelligibility, leading to better overall performance.
- **Works in real-time systems**
  With optimized architectures and hardware support, ANN models can process signals quickly enough for real-time applications such as communication and audio devices.

9. Limitations

- **Requires large training dataset:** To learn accurate noise patterns and generalize well, the network needs a significant amount of paired noisy and clean signal data, which may not always be easy to obtain.
- **High computational cost:** Training and running neural networks, especially with multiple layers, requires considerable processing power and memory compared to traditional filtering techniques.
- **Training can be time-consuming:** The learning process may take many iterations to converge, particularly when dealing with complex signals or large datasets.
- **Performance depends on data quality:** If the training data is noisy, biased, or not representative of real conditions, the network's performance may degrade and produce less accurate noise reduction.

10. 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.

11. Results and Discussion

ANN-based noise cancellation systems outperform traditional filters when dealing with non-stationary noise. The ability to learn from data allows the network to adapt to different environments and provide better signal clarity.

The model demonstrates that neural networks can effectively separate useful signals from noise, making them highly valuable in modern audio processing applications.

12. Conclusion

This project presented a conceptual model of an Artificial Neural Network designed for real-life noise cancellation. By systematically mapping the network architecture, identifying appropriate neuron types, and selecting a suitable learning law, the study demonstrated how ANN techniques can effectively filter unwanted noise and reconstruct a cleaner version of the original signal. The use of supervised error-correction learning allows the network to continuously compare its output with the desired signal and iteratively adjust its weights, leading to progressive improvement in performance.

The analysis highlights the practical significance of neural networks in modern signal processing applications. Unlike traditional filtering methods, ANN-based systems are capable of learning complex and dynamic noise patterns, making them more adaptable to real-world environments. This adaptability enables improved signal clarity, better user experience, and enhanced performance in various audio-related technologies.

Overall, the project provides a clear understanding of how neural networks can be applied to solve real-world engineering problems such as noise reduction. The concepts explored in this model serve as a strong foundation for further study in advanced areas like deep learning–based audio processing, adaptive filtering, and intelligent communication systems.

13. Future Scope

1. **Implement using deep learning frameworks**
   The proposed model can be developed using frameworks such as TensorFlow or PyTorch to enable efficient training, testing, and deployment on larger datasets.
2. **Use convolutional neural networks for audio spectrograms**
   Converting audio signals into spectrograms and processing them with CNNs can improve feature extraction and enhance noise reduction performance.
3. **Real-time deployment in embedded systems**
   Optimizing the model for low-power hardware can allow deployment in real-time devices such as headphones, hearing aids, and mobile systems.
4. **Combine with reinforcement learning for adaptive control**
   Integrating reinforcement learning can enable the system to adapt dynamically to changing noise environments and continuously improve performance through feedback.

14. References

1. Simon Haykin — Adaptive Filter Theory
2. Neural Networks and Learning Machines
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4. Audio Signal Processing Lecture Notes