The North African Journal of Scientific Publishing (NAJSP)
مجلة شمال إفريقيا للنشر العلمي (NAJSP)
E-ISSN: 2959-4820
Volume 3, Issue 3, 2025
Page No: 63-70
Website: https://najsp.com/index.php/home/index

SJIFactor 2024: 5.49	معامل التأثير العربي (AIF) 2024: 0.71	ISI 2024: 0.696

Artificial Neural Network-Based Active Noise Cancellation of Ambulance

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إلغاء الضوضاء النشط لصفارات الإسعاف باستخدام الشبكات العصبية الاصطناعية

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Received: June 05, 2025	Accepted: July 07, 2025	Published: July 19, 2025

Abstract:
This study investigates the use of artificial neural networks (ANNs) in Active Noise Cancellation (ANC) systems, demonstrating their effectiveness in reducing acoustic noise. By training the system with real-world audio data, such as ambulance sounds, the ANN-based approach successfully minimized noise while maintaining performance balance. The neural network design employed the tanh activation function across hidden and output layers, structured with three hidden layers (2, 3, and 5 nodes). Optimal performance was achieved through careful parameter tuning, including a learning rate of 0.001 and a momentum value of 0.9. The research underscores the capability of multi-layer perceptron (MLP) networks in accurate signal prediction and highlights the significance of parameter optimization. This adaptable MLP-based method holds promise for a wide range of signal prediction and noise cancellation applications.

Keywords: Artificial Neural Networks, Multi-Layer Perceptron, Signal Prediction, Active Noise Cancellation.

الملخص
تبحث هذه الدراسة في استخدام الشبكات العصبية الاصطناعية (*ANNs*) في أنظمة إلغاء الضوضاء النشطة (*ANC*)، مما يدل على فعاليتها في تقليل الضوضاء الصوتية. من خلال تدريب النظام باستخدام بيانات صوتية من العالم الحقيقي، مثل أصوات سيارات الإسعاف، نجح النهج القائم على الشبكات العصبية الاصطناعية في تقليل الضوضاء مع الحفاظ على توازن الأداء. استخدم تصميم الشبكة العصبية دالة تنشيط *tanh* عبر الطبقات المخفية والمخرجة، والمهيكلة بثلاث طبقات مخفية (2 و3 و5 عقد). تم تحقيق الأداء الأمثل من خلال ضبط المعلمات بعناية، بما في ذلك معدل تعلم 0.001 وقيمة زخم 0.9. يؤكد البحث على قدرة شبكات الإدراك الحسي متعدد الطبقات (*MLP*) في التنبؤ الدقيق بالإشارات ويسلط الضوء على أهمية تحسين المعلمات. هذه الطريقة القابلة للتكيف القائمة على *MLP* تعد بمجموعة واسعة من تطبيقات التنبؤ بالإشارات وإلغاء الضوضاء.

الكلمات المفتاحية: الشبكات العصبية الاصطناعية، المدرك متعدد الطبقات، التنبؤ بالإشارة، إلغاء الضوضاء النشط.

Introduction

Active noise control (ANC) has gained attention due to advances in computational power and electronics. Traditional ANC systems, relying on linear filters, struggle with nonlinear and nonstationary noise. Deep learning-based methods, like DNoiseNet, use atrous convolution and recurrent neural networks to improve ANC performance in environments such as construction sites, vehicles, and airplanes. An MLP-based secondary path estimator also addresses acoustic delay, enhancing noise reduction [1].

While effective in automotive settings, ANC's application in built environments remains limited. Research highlights its potential in construction machinery, noise barriers, and naturally ventilated buildings, stressing the need for intelligent solutions and stakeholder collaboration to handle complex noise variations [2]. Traditional ANC methods, based on adaptive signal processing, often fail in nonlinear conditions. Deep ANC treats ANC as a supervised learning problem, employing convolutional recurrent networks (CRNs) to generate anti-noise signals, achieving effective noise reduction across diverse scenarios [3].

Deep MCANC extends this to multi-channel ANC, optimizing control parameters for multiple canceling signals using CRN-based spectral mapping, demonstrating robustness against nonlinear distortions [4]. For construction sites, a deep-learning-based feedforward ANC controller mitigates transient machinery noise, balancing broadband attenuation and computational efficiency [5]. Another approach, the Harmonic Acoustic Pneumatic Source (HAPS), uses a controlled flow valve for duct noise cancellation, overcoming limitations of traditional loudspeakers in harsh conditions [6]. ANC has also been applied to windows for urban noise reduction, though challenges in system integration and energy efficiency remain [7].

ANC systems rely on superposition, generating anti-noise signals with equal amplitude and opposite phase. Recent developments focus on real-time adaptive filtering for dynamic environments [8]. For construction sites, CsNNet incorporates acoustic delays and nonlinear behaviors, achieving significant noise reduction [9]. Beyond noise control, ANC aids non-invasive sensing, using ultrasonic waves to identify fluid properties in enclosed containers by canceling structural noise and improving signal-to-noise ratios [10]. These advancements underscore deep learning's potential to revolutionize ANC, making it more adaptable and effective across diverse applications.

This research employs an artificial neural network (ANN) method to mitigate acoustic noise. The ANN predicts the noise, and the predicted value is inverted and combined with the incoming noise to diminish its intensity. A multilayer perceptron, known for its time series prediction capabilities, is utilized as the neural network model. The network was trained using noise samples, and a segment of current noise was fed into the system to facilitate prediction. Various tests were conducted to assess the system's performance, confirming that this approach effectively reduces acoustic noise.

Methods

This study enhances noise cancellation systems for ambulance sirens by leveraging the forecasting capabilities of artificial neural networks. The methodology for developing the system begins with an analysis of research requirements, followed by system design and implementation. The research approach is divided into clear steps: first, collecting ambulance siren data, which is then processed in MATLAB. The data is filtered using a Butterworth filter with a specific cutoff frequency, serving as both pre-processing and normalization. Next, a suitable neural network is designed and developed, requiring a thorough understanding of neural network principles, including algorithms and architecture. The final steps involve implementing the system, testing it against study requirements, and evaluating its performance.

ANN model design and programming

Designing an artificial neural network (ANN) follows a structured approach, typically consisting of five main stages:

- Data Collection: Acquiring the required dataset.
- Signal Pre-processing: Cleaning and normalizing the data.
- Network Design: Creating the architecture of the neural network.
- Network Training: Training the model using the processed data.
- Performance Evaluation: Testing the model to assess its effectiveness.

The initial stage in designing ANN models involved the gathering and preparation of sample data. According to the requirements, an ambulance siren audio file named "amb.m4a" was selected as the target sound for cancellation. The data was prepared by developing code to read and process it in MATLAB. Following data collection, two pre-processing steps were implemented to enhance the efficiency of ANN training. First, the raw data was filtered using a Butterworth filter with a 50 Hz cut-off frequency and a fifth-order design to eliminate randomness. The filtered data was then normalized to ensure consistent scaling, as combining variables with significantly different magnitudes could mislead the learning algorithm, causing smaller-scale variations to be ignored. Normalization ensured that all input features were equally weighted, improving the network's ability to learn effectively.

Implementation

When the network weights, biases, and target values are initialized, MATLAB's toolbox offers various functions such as narnet, narxnet, and newff to design the network. Key parameters to define include the number of hidden layers, nodes per layer, training function, transfer function, bias/weight learning function, and performance function. For this project, a feedforward multi-layer perceptron (MLP) network will be used. The network consists of three main layers: input, output, and hidden layers. The input layer, with ten nodes, is determined by the input data's characteristics, while the output layer has a single node as the network is designed for forecasting sound signals. The number of hidden layers and neurons is flexible but should be chosen carefully, as increasing neurons within a single hidden layer is often more effective than adding multiple layers. However, too many neurons can cause over fitting, where the model captures noise as valid patterns, while too few neurons can lead to under fitting, where the model fails to capture underlying data trends [11,12]. Figure 1 illustrates this concept, showing an estimated function f(x) in black, with under fitting g_1(x) in red, over fitting g_{10}(x) in blue, and a well-generalized fit g_3(x) in green.

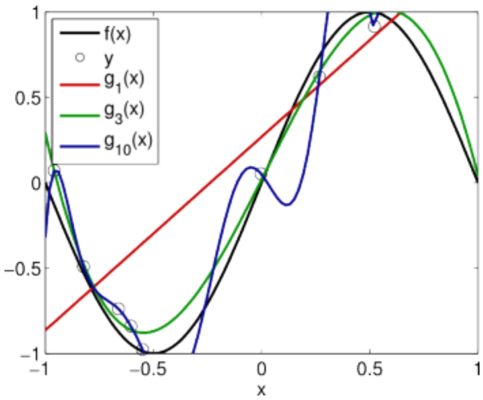


Figure 1: over-fitting, under-fitting and good fitting [11].

Underfitting happens when a predictor fails to model unseen data (testing data) accurately, while overfitting occurs when it performs well on training data but poorly on testing data. Balancing these issues is crucial for achieving a good fit, or generalization. A common approach is to begin with a large number of nodes in the hidden layer to maximize accuracy, despite increased training time, and then reduce nodes gradually while monitoring accuracy. This helps eliminate unnecessary complexity without significantly impacting performance. The proposed neural network design is shown in Figure 2.

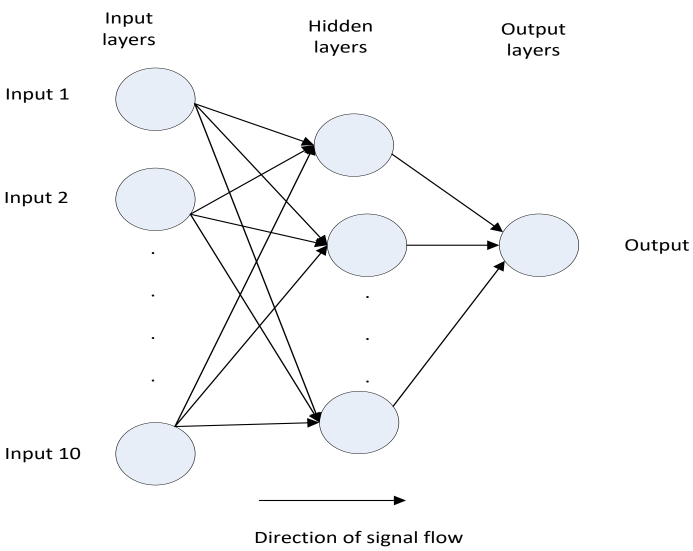
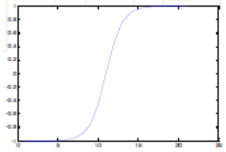
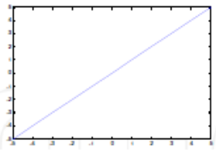
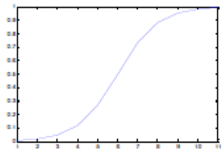


Figure 2: Neural Network Design.

During training, weight adjustments are made to minimize the difference between predicted and actual outputs. In this paper, the input data is an ambulance sound signal, which the neural network requires for training. Various training algorithms are explored to enhance the MLP system. MATLAB provides transfer functions, including Hyperbolic, Tangent Sigmoid (logsig), Linear (purelin), and Logistic Sigmoid (tansig), with their mathematical representations and graphs as shown in Table 1.

Table 1: The graphical and mathematical representation of functions.

Name of the Function	Hyperbolic Tangent Sigmoid	Linear	Logistic Sigmoid
The Graph of Function			
Mathematical Representation	$f(x) = \frac{e^x - e^{-x}}{e^x - e^{-x}}$	$f(x)$=x	$f(x) = \frac{1}{1 - e^{-x}}$

Preparing data before training a neural network is a critical factor for the success of any project. The process of signal preparation for neural network training consists of the following two stages:

- Filtering: Process the original signal using a Butterworth filter with a 50 Hz cut-off frequency and a fifth-order configuration.
- Normalization: Scale the data to a range of -1 to +1 to maintain uniformity and enhance the neural network's performance. Figure 3 illustrates the original signal in blue and the pre-processed signal in red.

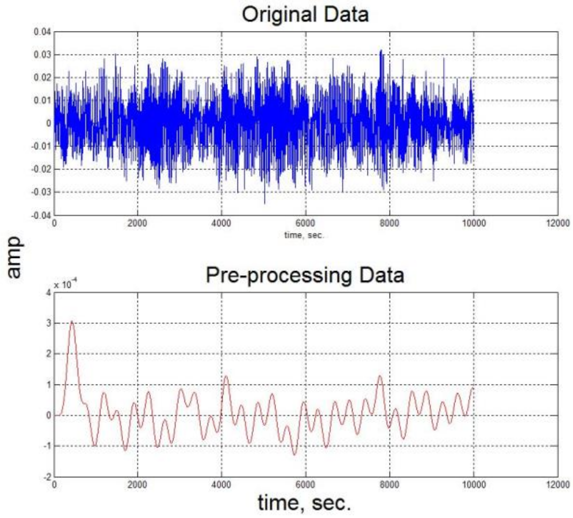


Figure 3: original and new Data.

Implementation of Neural Networks: With all required data (training, testing, and target data) prepared and ready, the next step is to implement the neural network using MATLAB-based code. Configuring MLP Parameters. The Hyperbolic Tangent (tanh) function is chosen as the training algorithm for this project. Key parameters for the neural network design have been initialized, with some to be fine-tuned during testing to achieve the best results. These parameters are: RMSE (error goal): 0.01

- Rate of Learning: 0.05
- Momentum: 0.1
- Hyperbolic Tangent (tanh) applied to the output and hidden layers is the activation function.
- 10 nodes make up the input layers.
- One node is the output layer.
- During testing, hidden layers, nodes, and epochs will be modified to maximise network performance.

Figure 4 presents the finalized flowchart detailing the step-by-step process for implementing the neural network and optimizing its performance.

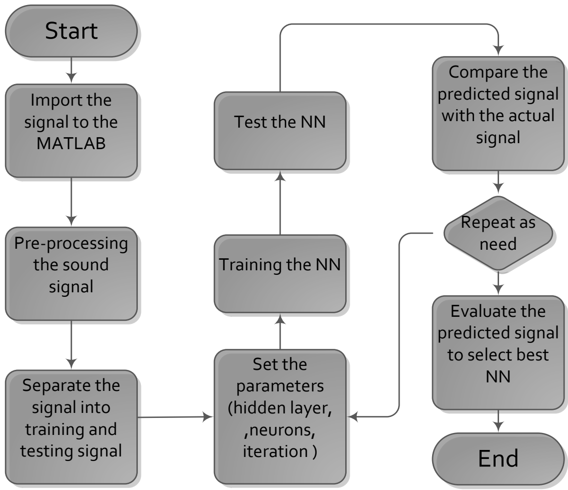


Figure 4: The final system flowchart**.**

Following multiple test cases to determine the best-performing network, the finalized parameters for the neural network design is outlined in Table 2.

Table 2: the setting parameters.

Parameter	Design
Activation Function (Output)	Hyperbolic Tangent
Activation Function (Hidden Layers)	Hyperbolic Tangent
Training Algorithm	Hyperbolic Tangent
Output Layer Size	1
Input Layer Size	10
Learning Rate	0.001
Momentum	0.9
Epochs	700
Number of Hidden Layers	3
Nodes Numbers	2, 3, 5

The network architecture consists of three hidden layers, containing 2, 3, and 5 neurons respectively, as depicted in Figure 5.

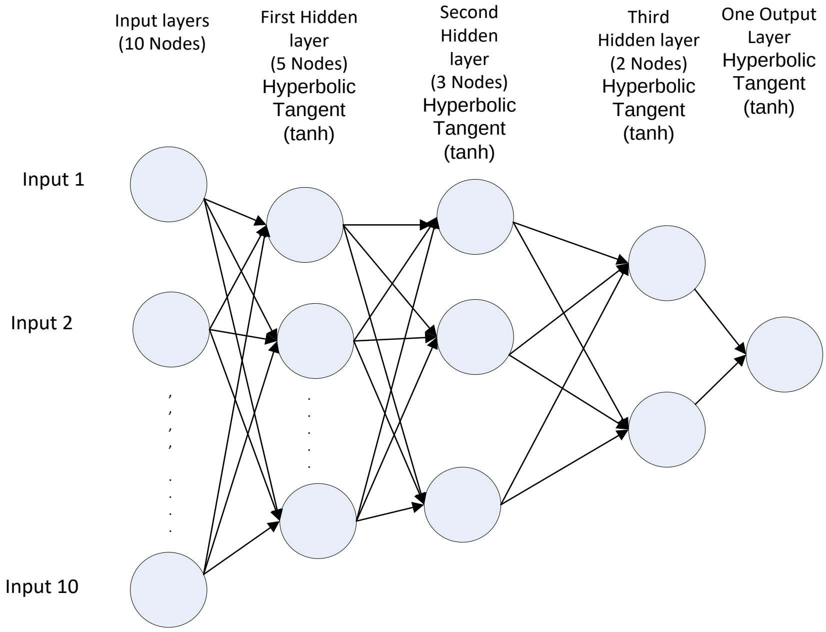


Figure 5: Neural network with three hidden layers and ten inputs.

Results and discussion

After extensive testing to determine the most effective design, the finalized model was reapplied, and the output signals were plotted. To confirm the design's reliability, four tests were conducted using different segments of the signal, demonstrating its capability to predict signals across varying lengths consistently. The neural network, configured with two hidden layers (2 and 3 neurons) and trained over 2500 epochs. This test aimed to validate the network's prediction accuracy and performance for this specific portion of the signal. The results were analyzed and visualized to confirm the design's capability in modeling the signal effectively.

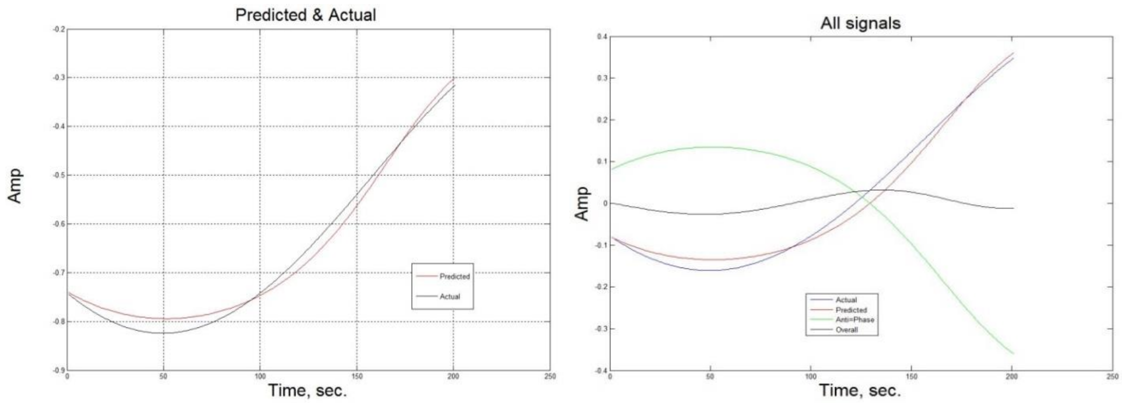


Figure 6: (samples 500 to 700) (a) tested and predicted signals. (b) actual, predicted and overall signals.

Figure 6 (a) illustrates the actual test signal alongside the predicted signal produced by the neural network. Figure 6 (b) provides a more detailed view, showcasing the actual test signal, the predicted signal, the anti-phased predicted signal (for noise cancellation), and the overall signal, which reflects the combined result of the noise reduction process. These figures highlight the network's ability to accurately predict and effectively reduce noise.

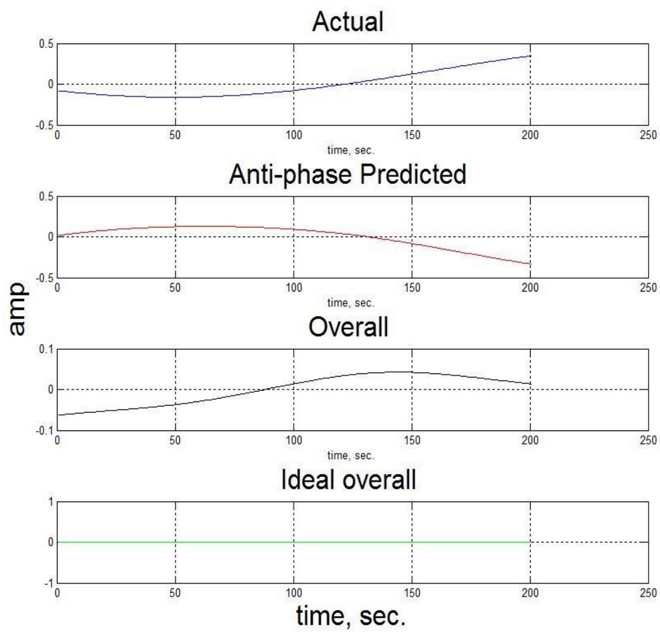


Figure 7: Actual, predicted, anti-phased, and overall signals plotted individually.

Figure 7 presents each signal actual, predicted, anti-phased predicted, and overall plotted in separate graphs for clear visualization and analysis. This allows for a detailed comparison of the signals and an assessment of the neural network's performance.

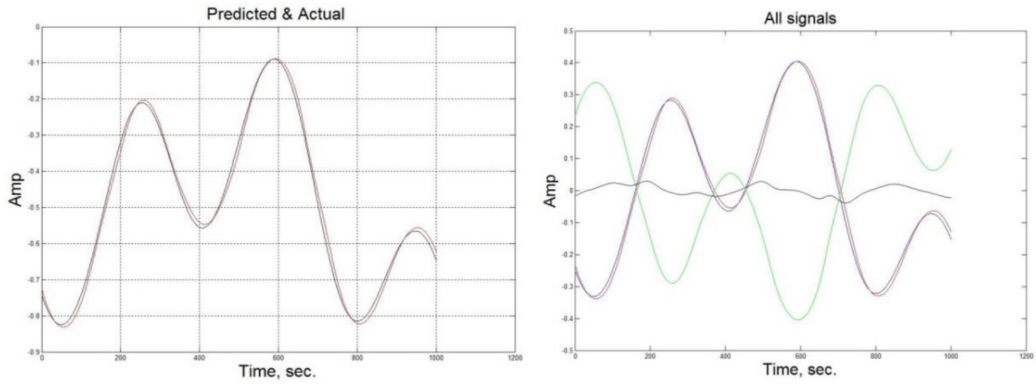


Figure 8: (samples 1000 to 2000) (a) tested and predicted signals. (b) Actual, predicted and overall signals.

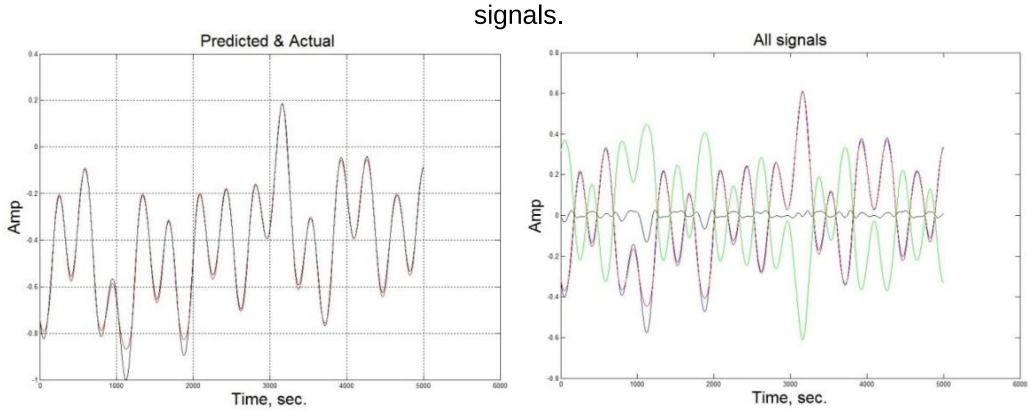


Figure 9: (samples 1 to 5000) (a) tested and predicted signals. (b) Actual, predicted and overall signals.

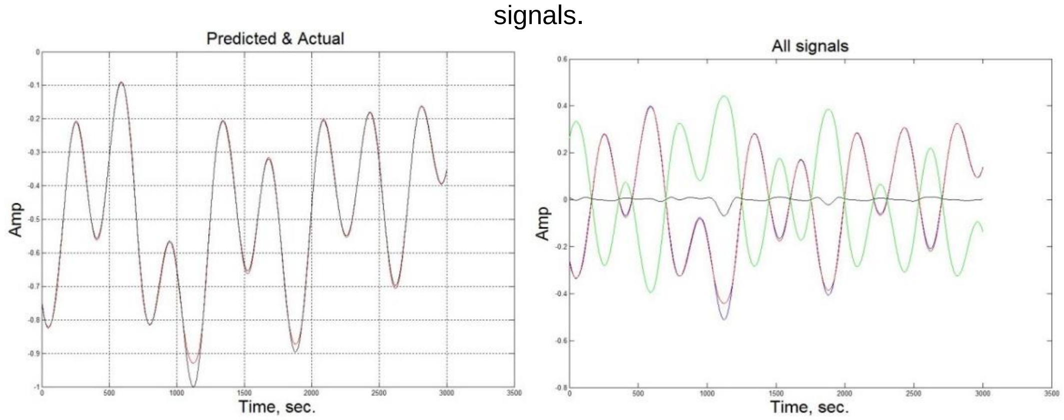


Figure 10: (samples 6000 to 9000) (a) tested and predicted signals. (b) Actual, predicted and overall signals.

Figures 8, 9, and 10 display the results of tested and predicted signals across various sample ranges. In Figure 8, panel (a) shows the tested and predicted signals for samples 1000 to 2000, while panel (b) illustrates the actual, predicted, and overall signals. Figure 9 presents the tested and predicted signals for samples 1 to 5000 in panel (a), with panel (b) showing the actual, predicted, and overall signals. Similarly, Figure 10 displays the tested and predicted signals for samples 6000 to 9000 in panel (a), and panel (b) depicts the actual, predicted, and overall signals.

Conclusion

The study focuses on an Active Acoustic Noise Cancellation (ANC) system using artificial neural networks (ANNs). While various noise reduction techniques exist, most rely on similar principles, generating signals that invert polarity or apply phase shifts to cancel noise. This study demonstrates the effectiveness of using ANN-based systems for noise elimination, particularly by training networks with real-world audio, such as ambulance sounds. The system successfully reduced noise and maintained balanced performance. The design of the neural network was crucial, with the tanh activation function used for both output and hidden layers. three hidden layers (2, 3, 5 nodes). The learning rate of 0.001 and momentum value of 0.9 was key to achieving optimal performance. The research highlights the capability of multi-layer perceptron (MLP) networks in predicting signals with reasonable accuracy, emphasizing the importance of parameter tuning in achieving effective results. The MLP method can be adapted for various signal prediction tasks.

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