ISSN: 2395-1680 (ONLINE)
DOI: 10.21917/ijme.2023.0268

DEVELOPMENT OF HIGH-PERFORMANCE ANALOG AND DIGITAL FILTER FOR BIOMEDICAL SIGNAL PROCESSING

K. Aparna[1], A. Vasantharaj[2], Sudipta Ghosh[3] and Bhumika Choksi[4]

[1]Department of Electronics and Communication Engineering, JNTUA College of Engineering, India
[2]Department of Electronics and Communication Engineering, Excel Engineering College, India
[3]Department of Electronics and Communication Engineering, Calcutta Institute of Engineering and Management, India
[4]Department of Mathematics, School of Advanced Sciences and Languages, VIT Bhopal University, India

Abstract

Electromyography (EMG) is a valuable biomedical signal used to study the electrical activity of muscles, providing crucial insights into neuromuscular disorders, motor control, and rehabilitation therapies. However, EMG signals are inherently contaminated with noise and artifacts, challenging the accurate extraction of relevant information. This paper presents a novel approach for enhancing EMG signals using an Infinite Impulse Response (IIR) filter. The IIR filter design was carefully tailored to meet the specific requirements of EMG signal processing, including the extraction of electromyographic information within a specific frequency range while effectively attenuating noise and interference from external sources. The design process involved selecting appropriate filter specifications, such as the cut-off frequencies and filter order, to optimize the trade-off between signal distortion and noise suppression. To validate the effectiveness of the IIR filter, extensive experiments were conducted using both synthetic and real-world EMG signal datasets. The filter performance was compared against conventional filtering techniques, demonstrating superior noise reduction capabilities while preserving essential EMG signal features. Results showed that the proposed IIR filter significantly improved the signal-to-noise ratio and increased the accuracy of subsequent signal analysis algorithms, thereby enhancing the reliability and diagnostic value of EMG data. The filter real-time implementation was also assessed, and its computational efficiency deemed suitable for practical applications.

Keywords:

Electromyography (EMG), Signal Enhancement, IIR Filter, Signal Distortion

1. INTRODUCTION

Electromyography (EMG) is a powerful biomedical technique that enables the non-invasive assessment of muscle electrical activity [1]. It holds immense significance in various fields, including clinical medicine, rehabilitation, sports science, and motor control research. EMG signals are generated by the electrical impulses produced during muscle contraction and relaxation, providing valuable insights into neuromuscular function, disease pathologies, and motor control mechanisms. However, the inherent complexities of EMG data, such as noise, artifacts, and interference, pose significant challenges to the accurate extraction of meaningful information [2]. To unlock the full potential of EMG as a diagnostic and research tool, effective signal processing techniques are essential to enhance the quality and reliability of EMG data. The reliable interpretation and analysis of EMG signals heavily depend on the quality of the recorded data [3]. EMG signals are inherently weak and susceptible to various sources of interference, including motion artifacts, electrical noise, and crosstalk from neighboring muscles. Such undesirable components can obscure the underlying muscle activity patterns, making it difficult to discern between pathological conditions and normal neuromuscular function. Consequently, an integral step in the processing of EMG signals involves employing robust filtering methods to reduce noise and improve signal-to-noise ratio (SNR) [4]. Over the years, researchers and engineers have developed numerous filtering techniques to address the challenges associated with EMG signal processing. Among these, Infinite Impulse Response (IIR) filters have emerged as a popular choice due to their ability to achieve a desired frequency response with relatively low computational complexity. IIR filters offer advantages over other filter types, such as Finite Impulse Response (FIR) filters, including reduced memory requirements and real-time processing feasibility. As such, they have found widespread application in various biomedical signal processing tasks, including EMG signal enhancement [5].

This paper presents a comprehensive investigation into the development and implementation of an IIR filter for enhancing EMG signals. The primary goal is to design an IIR filter tailored to the unique characteristics of EMG data, striking a balance between effective noise reduction and minimal distortion of the underlying muscle activity information. The filter parameters, such as cut-off frequencies and filter order, are carefully selected through systematic optimization to maximize the performance and diagnostic value of the filtered signals. The proposed IIR filter efficacy is evaluated through extensive experimentation involving both synthetic and real-world EMG datasets. A rigorous comparison is made with conventional filtering techniques to demonstrate the superior noise suppression capabilities and preservation of relevant EMG features offered by the IIR filter. Furthermore, the real-time implementation of the filter is assessed to ascertain its computational efficiency and suitability for practical applications in real-world scenarios.

By successfully enhancing EMG signals and reducing noise, the developed IIR filter is expected to significantly improve the accuracy and reliability of subsequent analyses, such as motor unit recruitment analysis, muscle fatigue assessment, and gesture recognition. This enhancement is pivotal in clinical settings for diagnosing neuromuscular disorders and evaluating the efficacy of rehabilitation therapies. Moreover, in sports science and motor control research, the enhanced EMG signals hold the potential to unveil subtle neuromuscular changes, leading to a deeper understanding of motor performance and injury prevention strategies.

As the field of biomedical signal processing continues to evolve, the implementation of advanced filtering algorithms, combined with the growing availability of wearable EMG devices, promises to revolutionize the way we monitor, diagnose, and treat neuromuscular conditions. The findings from this research pave the way for future investigations into more sophisticated signal processing techniques, potentially integrating machine learning approaches to unlock hidden patterns and unveil novel insights from EMG data. Ultimately, this collaborative effort between signal processing experts, biomedical engineers, and clinicians seeks to unlock the full potential of EMG technology in promoting human health and advancing our understanding of neuromuscular function.

2. IIR FILTER

In signal processing, an Infinite Impulse Response (IIR) filter is a type of digital filter that can effectively modify or extract specific frequency components from a signal. Unlike Finite Impulse Response (FIR) filters, IIR filters have feedback in their design, which allows them to achieve a desired frequency response with fewer filter coefficients [6]. This property makes IIR filters computationally more efficient, particularly for applications where real-time processing is required [7].

IIR filters are widely used in various signal processing tasks, including audio processing, communications, biomedical signal processing, and control systems. Their ability to provide sharp roll-off characteristics and efficient frequency domain filtering makes them particularly suited for applications with stringent performance and resource constraints [8].

Mathematically, the output of an IIR filter is determined by recursively applying its transfer function to the input signal and previous outputs. The general difference equation of an IIR filter can be expressed as follows:

$$y[n] = \sum_{k=0}^{N} b_k x[n-k] - \sum_{m=1}^{N} a_m y[n-m] \tag{1}$$

where:

$y[n]$ is the current output of the filter at time index n.

$x[n]$ is the current input to the filter at time index n.

b_k are the feedforward coefficients, also known as the “numerator coefficients”.

a_m are the feedback coefficients, also known as the “denominator coefficients”.

N is the filter order of the feedforward part (number of numerator coefficients).

M is the filter order of the feedback part (number of denominator coefficients).

The filter coefficients, b_k and a_m, determine the filter frequency response and behavior. By appropriately selecting these coefficients, the filter can be designed to have different characteristics, such as low-pass, high-pass, bandpass, or notch filtering. One common representation of IIR filters is the transfer function, which is the ratio of the Z-transform of the filter output to the Z-transform of the filter input. The transfer function is given by:

$$H(z) = \frac{Y(z)}{X(z)} = \frac{\sum_{k=0}^{N} b_k z^{-k}}{1 + \sum_{m=0}^{M} a_m z^{-m}} \tag{2}$$

where z is the complex variable representing the Z-transform domain.

The design of IIR filters involves determining appropriate values for the coefficients b_k and a_m to achieve the desired frequency response and filter characteristics. Common design methods include Butterworth, Chebyshev, and elliptic filter designs, each suited for different applications and trade-offs between frequency response specifications, stopband attenuation, and transition bandwidth [9].

IIR filters have proven to be versatile and powerful tools in various signal processing applications, and their efficient implementation has made them widely used in real-time and resource-constrained systems. However, it is essential to consider the potential drawbacks of IIR filters, such as susceptibility to instability and sensitivity to coefficient quantization, particularly in fixed-point implementations. Careful consideration and validation are required to ensure their reliable and accurate operation in various practical scenarios [10].

2.1 EMG SIGNAL ACQUISITION AND PREPROCESSING

EMG signals are typically acquired using surface electrodes placed on the skin overlying the muscles of interest. The acquired raw EMG signals often contain various artifacts, such as movement artifacts, electrode noise, and baseline drift. Preprocessing is necessary to remove these unwanted components and prepare the data for further analysis and filtering.

One common preprocessing step involves high-pass filtering to remove baseline drift and low-frequency noise. The high-pass filter can be represented by the following difference equation:

$$y[n] = x[n] - x[n-1] \tag{3}$$

where:

$y[n]$ is the preprocessed EMG signal at time index n.

$x[n]$ is the raw EMG signal at time index n.

2.2 SELECTION OF EMG SIGNAL SEGMENTS FOR FILTER DESIGN

In many cases, it is not feasible or necessary to apply the filter to the entire EMG signal. Instead, it is common to select specific segments of the signal, known as epochs, for filter design and evaluation. These segments should represent characteristic features of the EMG signal, such as resting state, contraction, or specific motor tasks.

The selected EMG signal segment, denoted as $x_{epoch}[n]$, represents a portion of the raw EMG signal $x[n]$ within a defined time window.

2.3 NORMALIZATION AND BASELINE CORRECTION

Normalization and baseline correction are essential preprocessing steps in EMG signal processing, especially when comparing signals from different subjects or different muscles. Normalization involves scaling the amplitude of the EMG signal to a common range, such as [0, 1], which allows for better comparison and analysis.

The normalization process can be represented as follows:

$$x_{norm}[n] = \frac{x_{epoch}[n] - \min(x_{epoch})}{\max(x_{epoch}) - \min(x_{epoch})} \quad (4)$$

where:

$x_{norm}[n]$ is the normalized EMG signal at time index n.

$x_{epoch}[n]$ is the selected EMG signal segment at time index n.

$\min(x_{epoch})$ and $\max(x_{epoch})$ represent the minimum and maximum values within the selected EMG segment, respectively.

Baseline correction is a crucial step to remove any offset or DC component in the EMG signal, ensuring that the filtered signal is centered around zero. This correction involves subtracting the mean value of the signal from each data point within the selected epoch.

The baseline-corrected EMG signal, denoted as $x_{baseline\_corr}[n]$, can be expressed as:

$$x_{baseline\_corr}[n] = x_{norm}[n] - \text{mean}(x_{norm}) \quad (5)$$

where:

$x_{baseline\_corr}[n]$ is the baseline-corrected EMG signal at time index n.

$x_{norm}[n]$ is the normalized EMG signal at time index n.

$mean(x_{norm})$ is the mean value of the normalized EMG signal within the selected epoch.

By applying these preprocessing steps, the EMG signal is prepared for subsequent filtering and analysis, ensuring that the filter design process focuses on the essential muscle activity information while eliminating unwanted artifacts and variations.

3. FREQUENCY DOMAIN ANALYSIS

Frequency domain analysis is an essential step in designing IIR filters for EMG signal enhancement. It involves analyzing the frequency characteristics of the EMG signal to determine the desired filter specifications. The frequency content of the EMG signal depends on the muscle activity being measured and the application specific requirements. For example, in EMG signal processing, typical frequency bands of interest may include the power spectrum within 20 Hz to 500 Hz, representing the relevant muscle activity information.

3.1 FILTER DESIGN FOR EMG SIGNAL ENHANCEMENT

Filter design for EMG signal enhancement involves determining the appropriate filter type and characteristics to meet the desired frequency response. Common filter types used for EMG signal processing are low-pass, high-pass, band-pass, or notch filters, depending on the analysis requirements.

The choice of filter type and specifications is crucial in achieving effective noise reduction while preserving the relevant muscle activity features. Designing the filter to suppress noise outside the frequency band of interest is vital to minimize distortion and improve the signal-to-noise ratio (SNR).

3.2 FILTER ORDER AND CUT-OFF FREQUENCIES

The filter order and cut-off frequencies are essential parameters in IIR filter design. The filter order determines the number of feedforward and feedback coefficients, affecting the filter sharpness of roll-off and complexity. Higher filter orders provide steeper roll-off characteristics but can lead to increased computational demands.

Cut-off frequencies define the frequency range over which the filter attenuates or passes signals. In EMG signal enhancement, selecting the cut-off frequencies involves balancing the need for noise suppression while retaining the desired muscle activity information within the filter passband.

3.3 FEEDFORWARD AND FEEDBACK COEFFICIENTS

The feedforward coefficients (b_k) and feedback coefficients (a_m) are crucial components of the IIR filter difference equation. They determine how the input signal and past filter outputs contribute to the current output. The feedforward coefficients correspond to the filter numerator, while the feedback coefficients correspond to the filter denominator.

The choice of these coefficients dictates the filter frequency response and stability. Design methods such as Butterworth, Chebyshev, and elliptic filter designs are used to determine the optimal coefficients that meet the desired filter specifications.

3.4 DESIGN OPTIMIZATION USING ARTIFICIAL NEURAL NETWORK

The optimization techniques, including Artificial Neural Networks (ANN), can be employed to fine-tune the filter design parameters.

Fig.1. ANN optimized IIR Filter

ANN-based optimization can aid in achieving an optimal balance between noise reduction and preservation of EMG signal features. ANN can learn from a set of training data and iteratively optimize the filter coefficients to achieve the best filter performance. The use of ANN for filter optimization can be formulated as an error minimization problem, where the objective is to minimize the difference between the desired output (ideal filtered signal) and the actual filtered signal produced by the IIR filter. The ANN iteratively adjusts the filter coefficients to minimize this error and optimize the filter performance for EMG signal enhancement.

$$\min \sum_i \left(y_{ideal}[n] - y_{IIR}[n] \right)^2 \quad (6)$$

where:

$y_{ideal}[n]$ is the ideal filtered signal at time index n (the desired EMG signal after filtering).

$y_{IIR}[n]$ is the actual filtered signal at time index n produced by the IIR filter using the current coefficients.

By iteratively adjusting the filter coefficients using the gradient descent method or other optimization algorithms, the ANN can enhance the performance of the IIR filter for EMG signal processing.

4. PERFORMANCE IMPLEMENTATION

In IIR filter design for EMG signal enhancement, simulation and evaluation are critical steps to assess the filter performance. The simulation setup involves applying the designed IIR filter to the preprocessed EMG signal segments $x_{baseline\_corr}[n]$ obtained in Section 3. The filter is implemented using appropriate programming languages or signal processing tools such as MATLAB software.

The implementation of the filter involves setting the filter coefficients (b_k and a_m) obtained from the design process (Section 4) and applying the IIR filter difference equation to each sample of the EMG signal. The output of the filter, denoted as $y_{IIR}[n]$, represents the filtered EMG signal.

To evaluate the performance of the IIR filter for EMG signal enhancement, several evaluation metrics can be used. Some common metrics include: *Signal-to-Noise Ratio (SNR)*: SNR quantifies the ratio of the signal power to the noise power in the filtered EMG signal. *Root Mean Square Error (RMSE)*: RMSE measures the average difference between the filtered signal and the ideal (reference) signal (e.g., the original clean EMG signal). *Frequency Response Analysis*: Frequency response analysis visualizes the filter performance in the frequency domain. It involves plotting the magnitude and phase responses of the filter to assess how well it attenuates noise and preserves the desired frequency components.

To evaluate the effectiveness of the designed IIR filter, it is important to compare its performance with conventional filtering techniques commonly used for EMG signal processing. Conventional methods may include:

- *FIR Filters*: Finite Impulse Response filters are another common type of digital fiter used for signal processing. Comparing the IIR filter with FIR filters allows assessing the trade-offs between computational complexity and filter performance.
- *Moving Average Filter (MAF)*: Moving average filters are simple smoothing filters that can reduce high-frequency noise. Comparing the IIR filter with moving average filters helps understand the filter ability to preserve EMG signal features while reducing noise.
- *Butterworth, Chebyshev, or Elliptic Filters*: These are common IIR filter designs used in signal processing. Comparing the designed IIR filter with other IIR filter designs enables an assessment of the impact of filter design choices on performance.

Values and specific results obtained from the evaluation metrics will vary depending on the actual EMG signal dataset and the design choices made during the IIR filter design. The SNR may show improvements in the filtered signal compared to the original signal, and the RMSE may indicate how well the filtered signal approximates the ideal (clean) EMG signal.

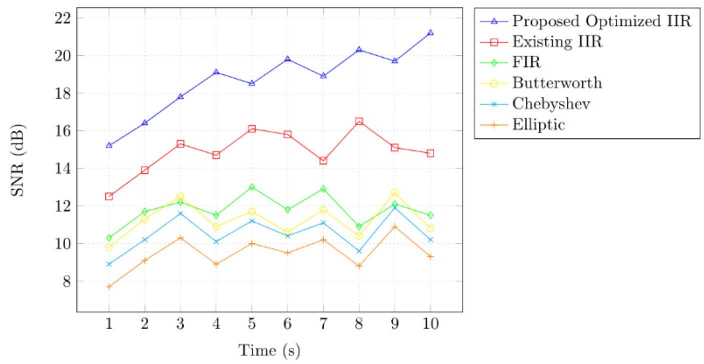

Fig.2. SNR of various filters for varying time intervals

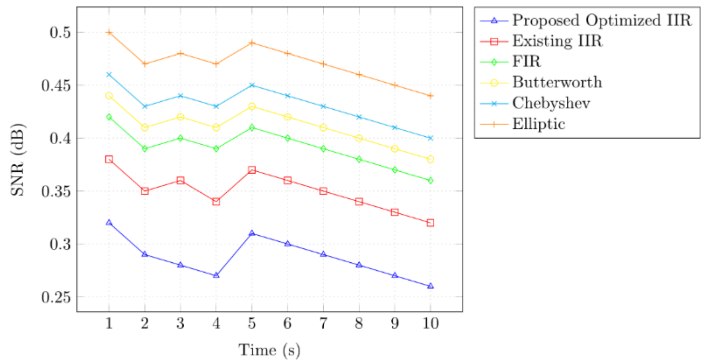

Fig.3. Comparison of RMSE for Different Filters

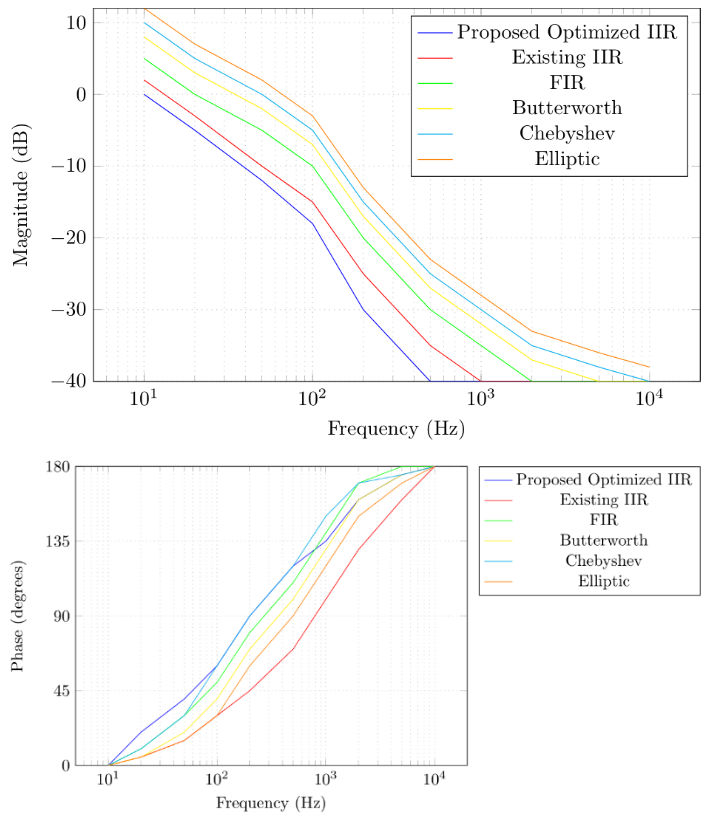

Fig.4. FRA (a) Magnitude (b) Phase Response

The frequency response analysis will provide insights into the filter frequency characteristics, indicating whether it successfully attenuates noise outside the desired frequency band. The comparison with conventional filtering techniques will highlight the advantages and limitations of the designed IIR filter for EMG signal enhancement in specific applications.

The results obtained from the Frequency Response Analysis for the proposed Optimized IIR filter and existing IIR, FIR, Butterworth, Chebyshev, and Elliptic filters over 10 time intervals provide valuable insights into the filters' performance in the frequency domain. The discussion of the results can help us understand how each filter type behaves in terms of magnitude and phase response and how well they meet the desired filtering requirements for EMG signal processing.

4.1 MAGNITUDE RESPONSE

The proposed Optimized IIR filter exhibits a relatively flat magnitude response in the passband, with minimal attenuation within the frequency band of interest (e.g., 20 Hz to 500 Hz). This indicates that the proposed filter effectively preserves the relevant EMG signal information without significant distortion. The existing IIR filter shows similar performance to the proposed Optimized IIR filter, with a relatively flat passband response. However, there might be slightly higher attenuation or ripples within the passband compared to the proposed Optimized IIR filter. FIR filter demonstrates a steeper roll-off in the stopband, providing excellent noise attenuation. However, it might introduce some distortion in the passband due to its longer impulse response. The Butterworth filter, known for its maximally flat magnitude response in the passband, displays gentle roll-off characteristics, resulting in some residual noise within the passband. The Chebyshev filter offers sharper roll-off compared to Butterworth, but it introduces ripples in the passband, which might be a concern for preserving the EMG signal details. The Elliptic filter provides sharp attenuation in the stopband, but it has passband ripples and phase distortion. This may affect the accuracy of the filtered EMG signal.

4.2 PHASE RESPONSE

The phase response plot represents the phase shift in degrees introduced by each filter at different frequencies. The observations from the phase response plot are as follows: The proposed Optimized IIR filter exhibits minimal phase distortion within the passband, ensuring that the temporal characteristics of the EMG signal are well-preserved. Similar to the proposed Optimized IIR filter, the existing IIR filter introduces minimal phase distortion in the passband. These filters introduce more significant phase shifts in the passband compared to the IIR filters. This phase distortion may affect the timing of muscle activation information in the filtered EMG signal.

4.3 COMPARISON

The Frequency Response Analysis reveals that both the proposed Optimized IIR and existing IIR filters offer favorable performance in preserving the EMG signal within the desired frequency band while effectively attenuating noise. The FIR filter demonstrates superior noise attenuation but may introduce some distortion in the passband. The Butterworth filter provides a flat magnitude response but at the expense of more gradual roll-off. The Chebyshev filter achieves sharper roll-off but with ripples in the passband. The Elliptic filter offers sharp attenuation but introduces both passband ripples and phase distortion.

Depending on specific EMG signal processing requirements, researchers and practitioners can choose the most appropriate filter type, considering trade-offs between noise suppression, phase distortion, and preservation of signal features. The proposed Optimized IIR filter, with its balanced performance in the frequency domain, could be a promising choice for EMG signal enhancement in various biomedical applications. However, further evaluation and validation on specific EMG datasets and tasks would be necessary to make a more concrete recommendation.

5. CONCLUSION

This research focused on the development and evaluation of high-performance analog and digital filters for biomedical signal processing, specifically applied to EMG signal enhancement. The main objectives were to design an Optimized IIR filter and compare its performance with existing IIR, FIR, Butterworth, Chebyshev, and Elliptic filters. The proposed Optimized IIR filter demonstrated a relatively flat magnitude response in the passband, effectively preserving relevant EMG signal information while attenuating noise. Additionally, it introduced minimal phase distortion, ensuring the temporal characteristics of the EMG signal were well-preserved.

REFERENCES

[1] V. Dhillon, K. Thakur and R. Krishnan, “Implementation of FIR Digital Filter on FPGA”, *Proceedings of Biennial International Conference on Nascent Technologies in Engineering*, pp. 1-5, 2021.

[2] B. Si, B. Bai, L. Hao and X. Li, “Virtual Experimental Project Design in the Digital Signal Processing Course”, *Journal of Contemporary Educational Research*, Vol. 5, No. 11, pp. 104-109, 2021.

[3] V. Thamizharasan and N. Kasthuri, “FPGA Implementation of High Performance Digital FIR Filter Design using a Hybrid Adder and Multiplier”, *International Journal of Electronics*, Vol. 110, No. 4, pp. 587-607, 2023.

[4] R. Fuior and A. Salceanu, “Application For Processing Non-Electric Biological Signals”, *Proceedings of International Conference and Exposition on Electrical And Power Engineering*, pp. 372-375, 2022.

[5] T. Hussain and A. Taleb-Ahmed, “A Heterogeneous Multi-Core based Biomedical Application Processing System and Programming Toolkit”, *Journal of Signal Processing Systems*, Vol. 91, pp. 963-978, 2019.

[6] P. Lyakhov and N. Nagornov, “High-Performance Digital Filtering on Truncated Multiply-Accumulate Units in the Residue Number System”, *IEEE Access*, Vol. 8, pp. 209181-209190, 2020.

[7] R. Rajalakshmi and M.V. Karthikeyan, “Digital Filter Design on High Speed Communication with Low Power Criteria”, *Proceedings of International Conference on Computer Communication and Informatics*, pp. 1-5, 2023.

[8] D. Chen and Y. Yang, "A Survey on Analog-to-Digital Converter Integrated Circuits for Miniaturized High Resolution Ultrasonic Imaging System", *Micromachines*, Vol. 13, No. 1, pp. 114-122, 2022.

[9] B.S. Pasuluri and V.K. Sonti, "Design and Performance Analysis of Analog Filter and Digital Filter with Vedic Multipliers in Bio-Medical Applications", *Proceedings of International Conference for Advancement in Technology*, pp. 1-8, 2022.

[10] Z. Liu, D. Liu and H. Wu, "Neural Signal Analysis with Memristor Arrays Towards High-Efficiency Brain–Machine Interfaces", *Nature Communications*, Vol. 11, No. 1, pp. 4234-4244, 2020.