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SIGNIFICANCE OF TRANSFORM TECHNIQUES AND MATHEMATICAL TOOLS IN BIOMEDICAL SIGNAL ANALYSIS

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ABSTRACT
Physiological processes involve extensive study of complex bio signals that can easily be analyzed by the use of mathematical tools. This research article devoted to study the predominant Mathematical tools and transform techniques that aids in the analysis of bio signals. This study also reveals the significance of certain tools like MATLAB and Python libraries that contribute in processing of bio signals and hence provide efficient diagnosis of fatal diseases.
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1 INTRODUCTION

Transmission of signals takes place through waves, images, electrical voltage, sound etc. Signals are composed of small components that vary with respect to time domain. Biological signals are complex in nature. It is of utmost important to analyze, modify and synthesize these signals so that it renders adequate information of the system studied.

This study deals with significant applications of Mathematical techniques like the Laplace Transforms, Fractional Fourier Transforms, Fourier Transform, Z-Transforms, Hilbert Transforms, Wavelet Transform, Empirical Wavelet Transforms and Fourier transforms that aids in decomposing these complex signals to simpler forms like the sinusoidal functions.

For example, Fourier transforms find several applications like image compression, Speech detection, Analysis of DNA, etc. Wavelet Transforms renders enhanced frequency resolution in comparison to Fourier transforms.

The wavelet functions are scaled or shifted to analyze signals. Wavelet bases are employed to recognize patterns and to determine tumors in brain [18].

Laplace Transform is used to convert complex differential equations to simpler algebraic equations. It plays a prominent role in the conversion of convolution operator to multiplication operator thus enabling easier computations to design complex systems. An extension of Laplace transforms was obtained to solve Integral and Integro–differential equation of Volterra and Caputo type [19].

Empirical Wavelet Transforms aids in handling signals that are non-stationary. It utilizes the concepts of wavelets and empirical mode decomposition (EMD) to extract information from signals. Fractional Fourier Transform helps to analyze signals in a fractional domain, allowing for time-frequency analysis with adjustable resolution. This transform provides enhanced localization of time and frequency domain and paves way for better filtration of noise. The Z transforms helps to handle discrete signals and analyze the stability of a system. It serves as an effective tool to analyze systems with time domain being continuous in nature. Hilbert Transform is a technique used to generate single-sideband signals, analyze instantaneous frequency and amplitude and extract envelope information from modulated signals. Here we focus on some of the mathematical and computational tools used to analyze signals.

2 PHYSIOLOGICAL SIGNALS

Physiological signals like Electrocardiogram (ECG), Electroencephalogram (EEG) popularly known as brain waves, Electromyogram, blood pressure etc have to be carefully analyzed to identify the functioning of vital organs in the human body. Pattern recognition of these bio signals provides valuable information to the physician for monitoring and diagnosis of diseases.

Signals and noise can be categorized into several types:

(a) Deterministic signal in noise: A blood pressure signal recorded via a fluid-filled catheter in the femoral artery is an example, where the signal is predictable but contaminated with noise.

(b) Deterministic signal synced to a cue: Somatosensory evoked potential recorded from the somatosensory cortex in response to an electrical stimulus is an example, where the signal is time-locked to a specific event.

(c) Stationary stochastic signal: A segment of EEG from the cortex with stable statistics and no specific morphology is an example, indicating a signal with consistent properties over time.

(d) Non-stationary stochastic signal: EEG recorded from an adult rat recovering from brain injury, showing bursts of activity with changing statistics, illustrates a signal with time-varying properties.

(e) Chaotic signal: An artificially generated signal that appears stochastic but originates from a deterministic dynamical system, highlighting the complexity of signal classification.

3 THE ROLE OF COMPLEX FUNCTIONS IN BIO SIGNALS

Complex functions serve as powerful tools in biomedical engineering in analyzing signals, processing of images and simulating various real-life phenomena. These functions also pave the way to design complex systems and biomedical devices.

In electrical engineering, complex numbers are used to represent impedance (Z) by combining resistance *(R)* and reactance *(X)* in AC circuits. In this context, resistance is the real component, while capacitive and inductive

impedances are represented by imaginary components. Specifically, inductive impedance is denoted as a positive imaginary value, whereas capacitive impedance is denoted as a negative imaginary value. Notably, the symbol "j" is used to represent the imaginary unit representing the current. Then the total impedance for resistance R takes the complex form, $Z = R + jX_i - jX_c$. Here X_i indicates the inductive impedance and X_c the capacitive impedance. Since voltage = impedance × current, voltage also takes complex form.

Unwanted distortions like artifacts arise from different sources. Biomedical signals are frequently intervened by artifacts and hence it is essential to remove them through filtration. Complex functions are used to represent a filter. For instance, the function $H(w) = \frac{1}{(1+jwRC))}$ denotes the transfer function for a low pass filter corresponding to a frequency w, resistance R and capacitance C.

4 MATHEMATICAL TRANSFORMS IN BIOSIGNALS

Now we explore predominant transform techniques that are widely used in analyzing Bio signals.

4.1 FOURIER TRANSFORM

The Fourier Transform is a cornerstone of biomedical signal processing, unlocking insights from physiological signals. It enables filtering, modulation, demodulation, and spectral analysis, transforming the field of biomedical engineering.

The Fourier transform for the function $x(t)$ defined in [10] is

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{(-i2\pi f t)}dt \quad (1)$$

where $x(t)$ is the input signal f is the frequency for time t.

Signals that vary with respect to time are decomposed into frequency components. Since biological signals are complex in nature, Fourier transforms aids in decomposing these signals to simpler forms like the sinusoidal functions.

In particular the study [10] revealed that noise and Arti crafts can be removed by the following:

- Low-pass filtering: removing high-frequency noise
- High-pass filtering: removing low-frequency artifacts
- Band-pass filtering: extracting specific frequency bands

ECG Signal Processing and Arrhythmia Detection

ECG signal processing is a vital part of biomedical signal processing, helping diagnose cardiovascular diseases. The Fourier Transform is key in this process, especially for detecting arrhythmias. By breaking down the ECG signal's frequency content, researchers can spot patterns that indicate arrhythmias. For instance, the Fourier Transform helps extract the ECG signal's power spectral density (PSD), revealing changes in heart rate variability (HRV).

The following table summarizes the results of a study on arrhythmia detection using ECG signal processing and the Fourier Transform:

Method	Accuracy
Fourier Transform + Machine Learning	95.6%
Time-Domain Analysis	80.2%
Frequency-Domain Analysis	92.1%

Processing and Brain-Computer Interfaces

EEG signal processing is a crucial part of biomedical signal processing, driving the development of brain-computer interfaces (BCIs). The Fourier Transform plays a key role in extracting and classifying features from EEG signals. By analyzing the signal's frequency content, researchers can pinpoint patterns tied to specific brain states or activities. For instance, the Fourier Transform extracts the EEG signal's power spectral density (PSD), revealing changes in brain activity during motor tasks. The following blockquote emphasizes the importance of the Fourier Transform in EEG signal processing.

"The Fourier Transform is a powerful tool for analyzing EEG signals, enabling the extraction of meaningful features that can be used to develop BCIs." - [21]

EMG Signal Processing and Muscle Fatigue Analysis

In EMG signal processing, the Fourier Transform is instrumental in analyzing muscle fatigue. By examining the frequency content of the EMG signal, researchers can identify subtle changes indicative of fatigue, such as shifts in the power spectrum. Specifically, the Fourier Transform is used to extract the Power Spectral Density (PSD) of the EMG signal, allowing for the detection of changes in muscle activity during sustained contractions, and providing valuable insights into muscle function and fatigue progression. The following equation used to compute the PSD using the Fourier Transform

$$P(f) = \frac{1}{T}|X(f)|^2$$

where $P(f)$ is the PSD, T is the duration of the signal, and $X(f)$ is the Fourier Transform of the EMG signal [10].

Applying Fourier Transform, researchers and clinicians extract valuable info from signals, aiding diagnosis, treatment development, and understanding of physiological processes. As the field advances, Fourier Transform will remain key to analyzing and interpreting biomedical signals.

4.2 WAVELET TRANSFORM

The wavelet transform [1] of the function $f(t)$ is given by

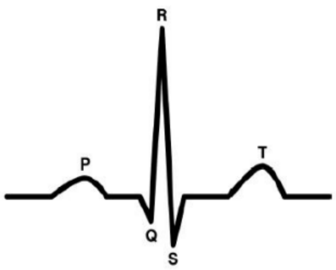
$$W(a, b) = \int_{-\infty}^{\infty} f(t)\psi_{a,b}(t)dt \quad (2)$$

Where $\psi_{a,b}(t)$ is the wavelet function, a is the scale, and b is the translation. Wavelets are either discrete or continuous in nature.

Here we present the algorithm proposed by the authors P. Thamarai and Dr. K. Adalarasu in the research article [1] which was a multi-scale wavelet based noise removal algorithm had been proposed for processing EEG, ECG and PPG signals. Also, the authos [1] shown that the algorithm not only removes the noise effectively but also keeps the time resolution of the input signal intact.

METHODOLOGY

A general ECG waveform generated is labelled as follows:



P wave −→Atrial depolarization

QRS −→ complex Ventricular depolarization

T wave −→ Ventricular repolarization

U wave −→ Repolarization of Purkinje fibers

Baseline −→ Polarized state

The ECG is measured as a multi- or single- channel signal, depending on the software. In arrhythmia analysis most effective one or two ECG leads are recorded or monitored to research lifestyles-threatening disturbances within the rhythm of the heartbeat.

The Standard 12-Lead ECG is recorded in the following stages

- ECG signal is traced in three various electrode positions.
- Standard Limb Leads (Bipolar Limb Leads) I, II, III
- Unipolar limb leads (Augmented Limb Leads)
- Unipolar chest leads (Standard Limb Leads) – I, II, III
- Every lead offers different reading.
- Total 12-reading is attained where standard leads-3, unipolar leads-3 and chest lead-6

4.2.1 CONTINUOUS WAVELET TRANSFORM

The Continuous Wavelet Transform (CWT) transforms a continuous signal into a redundant representation with two continuous variables namely translation and scale. This transformed signal offers a more interpretable and

valuable time-frequency analysis, allowing for the extraction of localized features and patterns that might be obscured in the original signal. The CWT's redundant representation provides a detailed, albeit data-intensive, view of the signal's time-frequency characteristics, making it a powerful tool for analyzing complex signals.
The continuous wavelet transform of the signal $y(t)$ is defined [1] as

$$T(c,d) = |d|^{-1/2} \int_{-\infty}^{\infty} y(t)\phi^{*}\left(\frac{t-c}{d}\right) dt \qquad (3)$$

where c and d are non-zero real numbers. Here c represents the dilating coefficient and d the translating coefficient. Here, ϕ^{*} is the conjugate of ϕ .
To analyze signals with multiple resolutions, the wavelet transforms serve as a powerful tool. Continuous wavelet transforms are more effective and versatile and facilitates computations of dynamic systems.

4.2.2 DISCRETE WAVELET TRANSFORM

The Discrete Wavelet Transform (DWT) is equivalent to filtering a signal through a bank of filters with non-overlapping bandwidths, where each filter's bandwidth increases by an octave (doubling of frequency range), effectively decomposing the signal into distinct frequency sub-bands.
The discrete wavelet transform [1] is defined in the form

$$W[e,f] = \sum_{m=-\infty}^{\infty} w[k]\varphi_{e,f}[k] \qquad (4)$$

Here $\varphi_{e,f}[k]$ is characterized as the window and f and e represent the translation parameter and contraction parameter respectively.
Physiological signals are denoised using a wavelet-based filtering approach [1]. Figure1 reveals the stages of the filtration of noise using this approach.

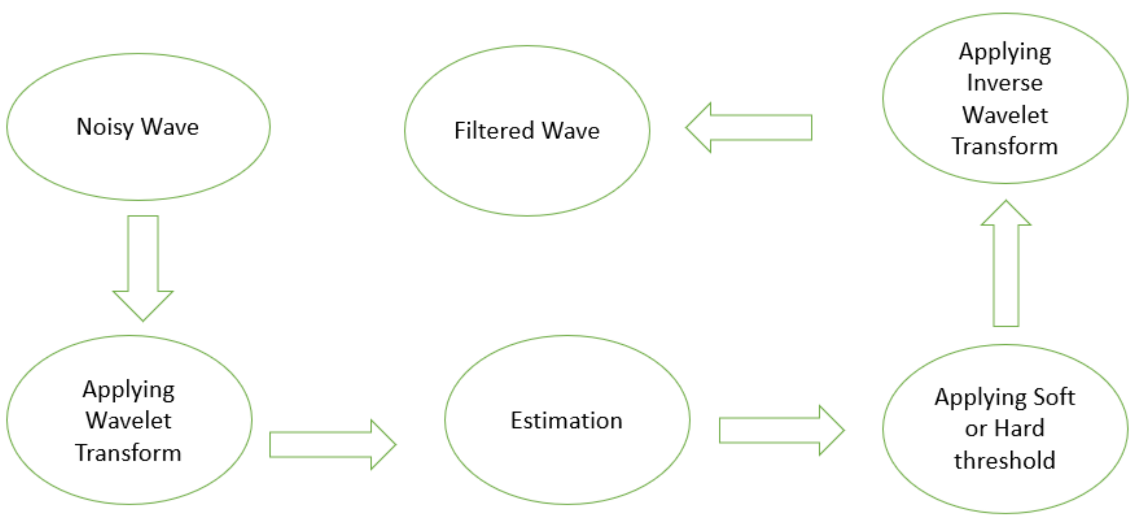


Figure 1: The schematic diagram of the mathematical process using wavelet transforms

Signals are processed by applying filters using mathematical transformations. The original and filtered signals are depicted in Figure 2

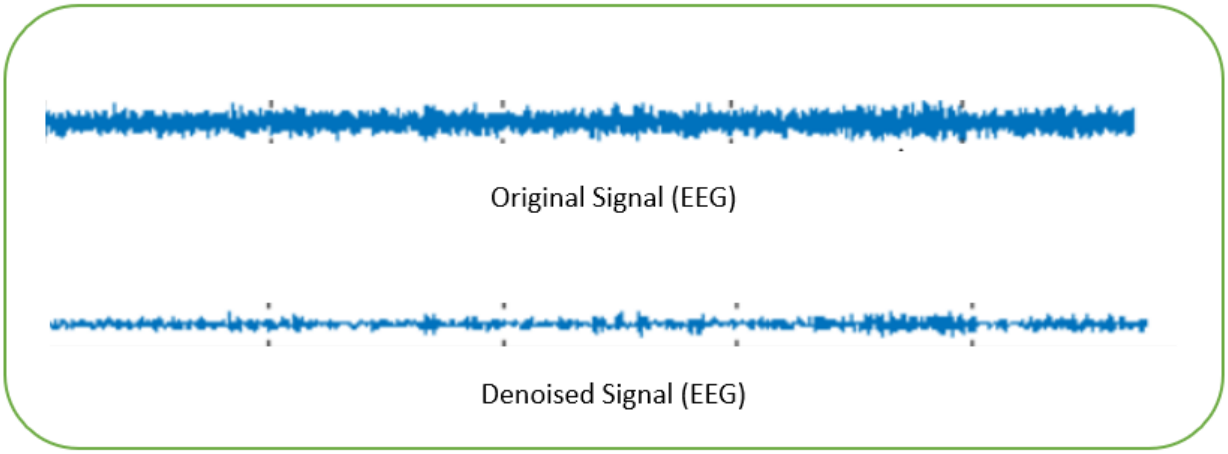


Figure 2: Original and Filtered signals

Wavelet based signal processing serves as an effective tool in

1. Analysis of Non-Stationary ECG signals
2. Classification of heartbeats recorded in ECG. The unusual pattern of these waves indicates the abnormal activity of the heart.
3. Noise reduction, feature extraction and compression.

Continuous wavelet transforms outperforms the Fourier transform by capturing localized features that might otherwise be obscured. In the observational study given in [2], wavelet analysis has been used to examine ECG frequency characteristics in 10 patients with controlled heart rates via right atrial pacing, aiming to identify local features and their rate dependence.

The complex Morlet wave function [2] is defined as

$$\psi(T) = \pi^{-1/4}\left(e^{i2\pi f_0 t} - e^{-(i2\pi f_0)^2 t}\right)e^{t^2/2} \quad (5)$$

Here f_0 is the frequency. This wave function examines both amplitude and phase and accommodates low central frequencies.

4.3 EMPIRICAL WAVELET TRANSFORMS

Empirical Wavelet Transforms is a powerful tool to study the characteristics of signals. A Filter bank is constructed by using the signals spectrum. This data driven technique uses the concept of Empirical Mode Decomposition and wavelet theory which has the following applications

- To detect normal breast tissue by analyzing spectral responses from breast tissues
- Identification of tumors in the brain by extracting features from Single Photon Emission Computed Tomography images of the brain
- Aids in the detection of neurological and cardiac disorders by the decomposition of signals of electroencephalogram (EEG) and electrocardiogram (ECG).

- EEG signals are analyzed to identify the pattern and aid in automated detection of alcoholism in patients.

4.4 LAPLACE TRANSFORMS

The Laplace transform, named after French mathematician Pierre Simon De Laplace, solves differential equations by converting signals via fixed rules. In digital signal processing, it involves receiving brief signals, extracting data, and outputting it, repeating the cycle. This finite, repetitive process underlies many systems, like GPS and traffic lights, despite their continuous operation. The Laplace transform is connected to the Fourier transform. But the Fourier transform decomposes a function or signal into its vibrational modes, whereas the Laplace transform resolves a function into its components. Both are used for solving differential and integral equations.

The Laplace transform [7] converts a time-domain signal into an s-domain (or s-plane) signal. The original time-domain signal is continuous, spans from negative to positive infinity, and can be periodic or aperiodic. This transform handles complex time domains.

The complex Fourier transform for the function $x(t)$ defined in [7] is

$$X(\omega) \ = \int_{-\infty}^{\infty} x(t)e^{(-j\omega t)}dt$$

The Laplace transform can be understood by multiplying the time-domain signal x(t) by an exponential term and taking the Fourier Transform

$$X(\sigma,\omega) \ = \int_{-\infty}^{\infty} [x(t)e^{-\sigma t}]e^{(-j\omega t)}dt$$

Methodology:

1. Start with the time-domain signal $x(t)$.
2. Multiply $x(t)$ by infinite number of exponential curves with varying decay constants σ.
3. Take the complex Fourier Transform of each weighted signal $X(\sigma,\omega) = \int_{-\infty}^{\infty} [x(t)e^{-\sigma t}]e^{(-j\omega t)}dt$
4. Plot each spectrum along a vertical line in the s-plane, with positive frequencies in the upper half and negative frequencies in the lower half.

The Laplace transform converts $x(t)$ to X(s) in the $s-$domain. To get values along a vertical line in the $s-$domain, multiply $x(t)$ by an exponential curve (decay constant σ) and take the complex Fourier transform. If $x(t)$ is real, the $s-$plane's upper half mirrors the lower half.

The two exponential terms can be combined and hence The Laplace transform of signal $f(t)$ for $t \geq 0$ is defined by

$$L(f(t) = F(s) = \int_{0}^{\infty} f(t)e^{-st}dt \qquad (7)$$

if the integral exists. Here s is a complex variable and t is the time variable.

The Laplace transform can be viewed as a two-step process:

1. Damping: multiplying the original signal by a decaying exponential curve e^{-st}, which helps converge the signal.

2. Fourier Transform: applying the Fourier transform to the damped signal, decomposing it into frequency components.
This perspective highlights the Laplace transform's role in analyzing signals with exponential growth or decay.

INVERSE LAPLACE TRANSFORMS
Inverse Laplace Transform enables the conversion of complex frequency domain function to the time domain. It is defined as $f(t) = L^{-1}(F(s))$ and it helps to recover the original function.
Applications

1. Design of digital filters in the reduction of noise and artifacts from ECG signals
2. Analyze the efficiency of the design of biomedical devices like biosensors
3. Aids in Bio mechanics-Design of assistive mobility devices

4.5 FRACTIONAL FOURIER TRANSFORMS
This transform uses the fractional powers [8] and is defined as

$$F(u) = \int_{-\infty}^{\infty} f(t) K_{\emptyset}(t,u)\, dt$$

Here $K_{\emptyset}(t,u)$ called the Kernel is defined as

$$K_{\emptyset}(t,u) = \begin{cases} \sqrt{\frac{1-jcot\emptyset}{2\pi}}\, e^{j\,\frac{t^2+u^2}{2}} cot\emptyset - jutcsc\emptyset, if\ \emptyset\ is\ not\ a\ multiple\ of\ \pi \\ \delta(t-u), if\ \emptyset\ is\ a\ multiple\ of\ 2\pi \\ \delta(t+u), if\ \emptyset + \pi\ is\ a\ multiple\ of\ 2\pi \end{cases} \quad (8)$$

Fractional Fourier Transforms has the capacity to capture non stationary signals and finds application in detection, filtration and extraction of signals.

4.5.1 Characteristics of the Fractional Fourier transforms:
Fractional Fourier Transforms uses the fractional roots of unity of $e^{(2\pi i\alpha)}$ for some arbitrary value α whereas the Discrete Fourier transform uses the integral roots of unity of $e^{(-2\pi i/n)}$. This transforms aids to analyze sequences of non integer periodicities and to identify signals having drifting frequencies that are linear in nature.

4.5.2 Feature Extraction and Fractional Fourier transforms
Fractional Fourier transforms (FrFT) performs Feature Extraction through these stages.
1.Intermediate domain representation is obtained by modifying the order of the FrFT.
2.FrFT exhibits a multidomain feature extraction and hence enhances accuracy in classification.

Process of Feature Extraction:
Step 1. A series of multi order Fractional Fourier Spectra is obtained using FrFT to the signals with different orders.
Step 2. Significant features like phase information are extracted from this spectra.
Step 3. Statistical measures like Mean, Variance, Kurtosis, Entropy, Energy etc are identified from the frequency domain representation.

Step 4. The desired features are extracted based on the accuracy of an appropriate predictive model like Least Square Supportive Vector Machine (LSSVM).

In particular, the applications of FrFT in the detection of signals as given in the study [12].

METHODOLOGY:

- Emotion detection is obtained through arousal and valence from the signals .
- The features that are extracted are processed through Support Vector Machine and the emotions are classified.
- The phase information obtained from FrFT coefficients using ECG signals and GSR was identified and the emotion recognition accuracy was found to be 78.32% and 76.83% respectively. The study also indicates better accuracy for ECG signals.

5 Z - TRANSFORMS

Z transforms play a prominent role for processing data sequences. The difference equations described in the system are converted into algebraic equations and hence Z transforms pave the way for easy computations.

If $x(n)$ is a discrete data sequence then Z transforms of $x(n)$ is defined as follows

$$Z(x(n)) = X(z) = \sum_{n=0}^{\infty} x(n)\, z^{-n} \tag{9}$$

is the one-sided Z transform for the sequence $x(n)$. Here z is a complex variable given by

$z = re^{jw}$ where r is the radius of a circle.

Z-transforms is utilized in biomedical signal processing, for example, to isolate the alpha band (8–13 Hz) from EEG signals using a digital bandpass filter designed via Z-transform, aiding in the detection of relaxed mental states.

Steps:

1. EEG signals are recorded using scalp electrodes with a sampling rate typically 128 Hz or 256 Hz.
2. Artifacts such as noise are removed
3. Z-Transform are used to design the filter by solving the difference equation $y[n] = a_1\, y[n-1] + a_2 y[n-2] + b_0 x[n] + b_1 x[n-1] + b_2 x[n-2]$
   and Z-transform $H(z) = \frac{Y(z)}{X(z)} = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 - a_1 z^{-1} - a_2 z^{-2}}$ (10)
4. Use the convolution of the Z-domain:
   $Y(z) = H(z).X(z)$
5. Computation of PSD.
6. The extracted features are then used to classifying mental states.

6 HILBERT TRANSFORMS

Hilbert Transforms [9] plays a vital role in the field of signal processing in designing filters and synthesizing signals.

$$H[g(t)] = g(t) * \frac{1}{\pi t} = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{g(\tau)}{t-\tau}\, d\tau = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{g(t-\tau)}{\tau}\, d\tau \tag{11}$$

Hilbert Transforms is a powerful tool used to analyze non-linear and non-stationary signals. It finds a wide range of applications in analyzing physiological signals.
Interpretation of QRS of ECG provides valuable information of the functions of the heart. Hence extracting QRS of an ECG paves way for enhanced diagnostics to clinicians.
In [14], a methodology has been developed to detect the QRS of ECG. As the QRS resembles a sine wave, it can be defined as $x(t) = sint.$ An analytic signal $z(t) = x(t) + i\,H(x(t))$ is constructed.
Since $H(x(t)) = H(sint) = -cost;\ z(t) = sint - icost;\ z(t) = -ie^{-it}$, this indicates $z(t)$ is the parametrization of the unit circle in the Argand plane. Hence extraction of QRS in [14] reveals the following stages:

Step1: The ECG signal at first is filtered and noises are removed so that it exhibits a smooth curve.
Step2: The ECG wave must have mean zero for further analysis. Nonzero mean is converted to zero mean by detrending.
Step3: The Hilbert Transforms is used to convert the detrended wave to analytic signal.
Step4: Hence $z(t) = ECG(t) + iH(ECG(t))$ is analysed along the parametric interval
The extracted QRS are studied by Principal Component Analysis or any other suitable method to classify the ECG signal for various irregularities in heartbeats.

7 TOOLS AND SOFTWARE

We present certain predominant tools used in bio signal analysis here.
1. MATLAB: A popular software for signal processing, analysis and pattern recognition.
The Signal Processing Toolbox in MATLAB plays a prominent role in the design and analysis of filters. This toolbox generates functions to extract features from different signals related to frequency and time domain.
The following apps use Matlab script and serve to reproduce and automate information.

1. Signal Analyzer App
2. Filter Design App
3. Neural Net Pattern Recognition App

Signal Analyzer App enables to visualize and process signals related to time and frequency domains[20].
Filter Designer App enables the user to handle finite and infinite impulse filters. Filters can be used to modify the frequencies of time domain signals to get the desired results as illustrated in [19].
1.Neural Net Pattern Recognition App generates functions to deploy with the tools MATLAB Compiler and MATLAB Code and later on processed with Simulink Coder.
2. Python: A programming language with libraries like NumPy, SciPy, and Pandas for signal processing and analysis.
Scipy library plays a vital role in digital signal processing with several tools like wavelet transforms, time frequency analysis available for spectral analysis.

NumPy is a free library in PYTHON that can handle multidimensional arrays and functions in linear algebra, Fourier transforms and matrices.

BioSig is a library that enables us to process biomedical signals with Matlab, Python and Octave.

3. Specialized Software: Software like LabVIEW, Spike2, and AcqKnowledge serve for data acquisition and data analysis.

CONCLUSION

This study explored certain prominent mathematical tools and transform techniques that facilitate the analysis of complex bio signals, including Fourier Transform, Laplace Transform, Wavelet Transform, Hilbert Transform, and Z-Transform. These methodologies, coupled with machine learning and statistical analysis, enable researchers to extract valuable insights from biosignals. Notable contributions from authors like P. Thamarai , K. Adalarasu in [1], M.K. Stiles et al. [2], Ganesh Naik [3], K. Ramesh et al. [7] who developed a worthy methodology for denoising and analysing the signals. Also, this study has highlighted the significance of software tools like MATLAB and Python libraries (e.g., NumPy, SciPy, Biopython) in processing biosignals and diagnosing fatal diseases.

Advanced techniques like Hilbert-Huang Transform, Graph Signal Processing, Deep Learning-based methods (e.g., CNNs, RNNs) offer deeper insights into complex biosignals. Fractal Analysis and Nonlinear Dynamics reveal hidden patterns, which also can be studied in future.

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