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Investigating Abdominal Electrocardiogram (ECG) Signals using Scalogram Analysis for Accurate Characterization

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Abstract

The abdominal electrocardiogram (ECG) has emerged as a promising non-invasive technique for cardiac monitoring. However, accurately characterizing aECG signals remains challenging due totheir complex nature and susceptibility to noise. In this study, we investigate the application ofContinuous Wavelet Transform (CWT) combined with scalogram analysis for the accuratecharacterisation of ECG signals. We propose a novel framework that leverages the time-frequency analysis capabilities of CWT and the visual representation provided byscalogram analysis to extract valuable features from ECG signals. Through extensive experimentation on a dataset of ECG recordings, we demonstrate the efficacy of our approach in accurately characterizing various cardiac events, including P-wave detection, QRS complex identification, and T-wave analysis. The proposed method exhibits superior performance compared to traditional time-domain or frequency-domain analysis techniques.

Furthermore, we explore the impact of different wavelet functions and CWT parameters on the characterization accuracy. Our findings highlight the potential of CWT/scalogram analysis as a robust tool for precise and reliable characterization of ECG signals. The outcomes of this research hold great promise for advancing the field of non-invasive cardiac monitoring and havesignificant implications for improving the diagnosis and treatment of cardiovascular diseases.

Keywords: Abdominal electrocardiogram(ECG) signals, Time-Frequency analysis, Continuous Wavelet Transform (CWT), Scalogram Analysis, P-wave detection, QRS complex identification,T-wave analysis, wavelet functions, cardiovascular diseases.

Introduction:

The abdominal electrocardiogram (ECG) has gained significant attention as a non-invasive technique for cardiac monitoring. Unlike traditional surface ECG, abdominal ECG offers the advantage of capturing cardiac electrical activity from electrodes placed on the abdomen, providing a broader view of cardiac signals and potentially overcoming limitations associated with body fat, muscle activity, and electrode placement. However, accurate characterization ofabdominal ECG signals remains challenging due to their complex nature and susceptibility to noise.

In recent years, various signal processing techniques have been explored to extract meaningful information from ECG signals. One promising approach is the utilization of Continuous WaveletTransform (CWT) combined with scalogram analysis. CWT is a time-frequency analysis technique that enables localized analysis of signal components, capturing both temporal and spectral information. Scalogram analysis, on the other hand, provides a visual representation of the time-frequency content of signals, allowing for intuitive interpretation and identification ofrelevant features.

In this research paper, we aim to investigate the effectiveness of scalogram analysis for the accurate characterization of abdominal ECG signals. We propose a novel framework that leverages the time-frequency analysis capabilities of CWT and the visual representation providedby scalogram analysis to extract valuable features from abdominal ECG signals. Our objective is to enhance the identification and analysis of key cardiac events, such as P-waves, QRS complexes, and T-waves.

Through extensive experimentation on a dataset of abdominal ECG recordings, we evaluate theperformance of our proposed approach and compare it with traditional time-domain or frequency-domain analysis techniques. Additionally, we explore the impact of different waveletfunctions and CWT parameters on the characterization accuracy. The outcomes of this researchhave the potential to significantly advance the field of non-invasive cardiac monitoring by providing a robust and accurate method for characterizing abdominal ECG signals.

Accurate characterization of abdominal ECG signals can greatly contribute to the diagnosis and treatment of cardiovascular diseases. It can aid in the early detection of cardiac abnormalities, monitoring of cardiac function, and assessment of treatment efficacy. Furthermore, the proposedmethod holds promise for improving overall diagnostic accuracy and patient care in the field of cardiology.

Overall, this research paper aims to contribute to the existing literature by investigating and validating the effectiveness of scalogram analysis in accurately characterizing abdominal ECGsignals. The results of this study have the potential to significantly impact the field of non-invasive cardiac monitoring and pave the way for future advancements in cardiacdiagnostics and treatment.

Electrocardiogram (ECG Signal):

The electrocardiogram (ECG) signal represents the electrical activity of the heart and plays a crucial role in diagnosing cardiovascular diseases. However, the ECG signal presents challengesdue to its non-stationary nature, low amplitude (typically ranging from 10μV to 5mV), and low-frequency content (0.05Hz to 100Hz). Cardiac events in an ECG are associated withalphabetical labels as shown in Fig.1

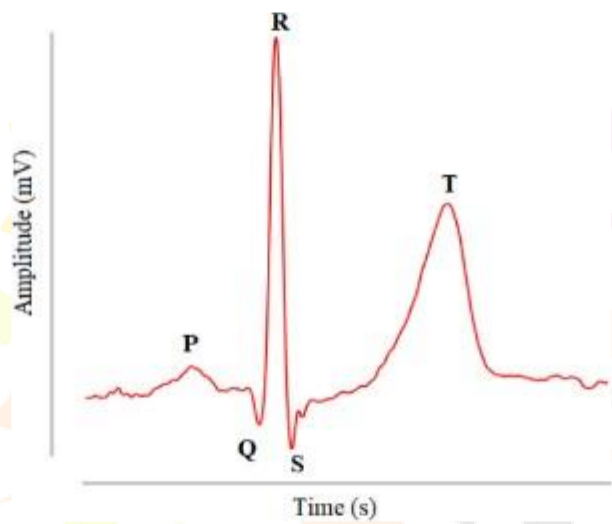


Fig.1: ECG signals & it's components

Figure 2 illustrates the power spectral density of the electrocardiogram (ECG) and its respective components. The visual representation clearly demonstrates that the energy of the ECG is spreadacross the frequency range of 2 to 40 Hz, encompassing the typical frequency range of clinical sounds.

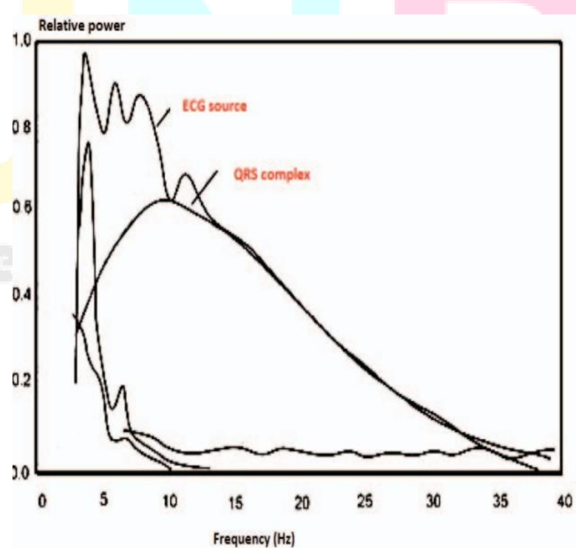


Fig.2: ECG signal & its components' spectral density curve

Continuous Wavelet Transform (CWT):

I. Theory

a) Wavelet:

A wavelet Fig .3 is a function ψ(t) which satisfies the following conditions[6,5, 9,10]

Fig.3: Morlet Wavelet

- Wavelet must have finite energy:

$$\epsilon = \int_{-\infty}^{+\infty} |\psi(t)|^{2} \, dt < \infty \qquad (1)$$

- The Fourier transform of ψ(t):

$$\widehat{\psi(f)} = \int_{-\infty}^{+\infty} \psi(t) e^{-i2\pi f t} \, dt \qquad (2)$$

- Admissibility constant:

$$Q = \int_{0}^{+\infty} \frac{|\widehat{\psi(f)}|^{2}}{f} df \qquad (3)$$

b) Wavelet Transform:

$$\psi_{a,b} = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \qquad (5)$$

For a continuous signal, the wavelet transform is defined as:

$$T(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \psi^{*}\left(\frac{t-b}{a}\right) dt \qquad (4)$$

The equation presented incorporates both the dilated and translated wavelet, denoted as ψ((t-b)/a), and the signal x(t).

The Signal Energy:

For a particular scale (a) and location (b), the extent to which the signal energy contributes isdescribed by the two-dimensional wavelet energy density function.

$$€(a, b) = |T(a, b)|^2 \qquad (6)$$

A graphical representation of €(a,b) is com monly referred to as a ***Scalogram*** or a **Time Scales Image.**

II. Wavelets used in Signal Processing:

The Continuous Wavelet Transform (CWT) [11] possesses the ability to identify abrupt ariations and oscillatory patterns present in a signal. To properly analyze and interpret the coefficients derived from the CWT, it is crucial to take into account the following fundamentalprinciples:

- ***Cone of influence:*** The CWT coefficient at a specific point can be influenced bysignal values at distant points, depending on the scale which is considered.

- ***Detection of abrupt transitions:*** Wavelets play a pivotal role in identifying sudden shifts or changes within a signal, making them indispensable in detection tasks that involve abrupt transitions. Their ability to capture localized information at different scales enables effective detection and analysis of such variations in thesignal.

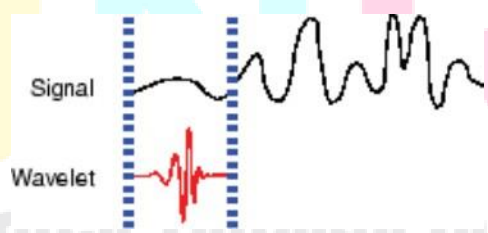
- ***Detection of smooth signal features:*** When signal features exhibit smooth characteristics, they tend to generate relatively larger wavelet coefficients at scales where the oscillation in the wavelet aligns most effectively with the signalfeature.

The basic algorithm for the continuous wavelet transform (CWT) is:

1. Begin by selecting a wavelet and comparing it to an initial segment of the original signal.

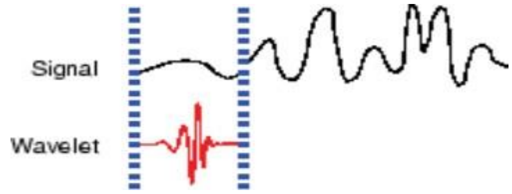
2. Determine a correlation value, denoted as C, which quantifies the level of similarity betweenthe wavelet and the selected segment of the signal.

3. It is important to note that the coefficients obtained through the Continuous Wavelet Transform (CWT) are influenced by the choice of the analyzing wavelet. Consequently, when computing the CWT for the same signal using different wavelets, the resulting coefficients willvary. This dependency on the wavelet used is explicitly discussed in the context of Continuousand Discrete Wavelet Transforms.



C= 0.0102

4. Shift the wavelet to the right and repeat steps 1 and 2 until you've covered the whole signal.



C=0.0102

To facilitate potential comparisons, three wavelets can be considered: ***Gaus1*** and ***Gaus2***, derived from the Gaussian function, and the complex Morlet wavelet, ***CMOR***. It is worth noting that ***Gaus2*** is also termed 'the Hat Mexican wavelet' and is commonly referred to as ***mexh.***

Methods:

I. ECG Recordings:

Our objective is to analyze and describe the characteristics of the abdominal electrocardiogram(ECG) solely using the Continuous Wavelet Transform (CWT) as a mathematical tool. Since real-time data was not accessible, we opted to work with a synthetic dataset. To create this

synthetic dataset, we utilized a synthetic ECG data generator equipped with 34 electrode channels, with 32 of them placed on the abdomen and the remaining 2 acting as thoracic references. Through this approach, we effectively generated a synthetic dataset for further

analysis and investigation of the abdominal ECG. The alignment of electrode channels is as follows:

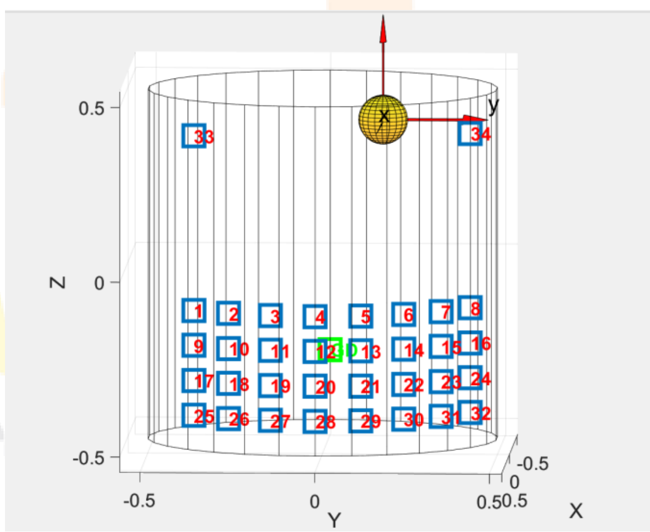


Fig.4: Alignment of electrode channels for synthetic ECG generator

The synthetic signals generated for this study had a sampling frequency of 1 KHz (1000 Hz), capturing a high-resolution representation of the abdominal ECG.

MATLAB 2022b, equipped with the wavelet toolbox, was utilized on a Windows 11 operatingsystem for the analysis. All 32 abdominal channels were thoroughly examined for evaluating ECG signal outputs. After careful evaluation, a subset of channels with clearer outputs was
selected for further analysis, prioritizing the channels that provided more distinct and reliable ECG signals compared to others.

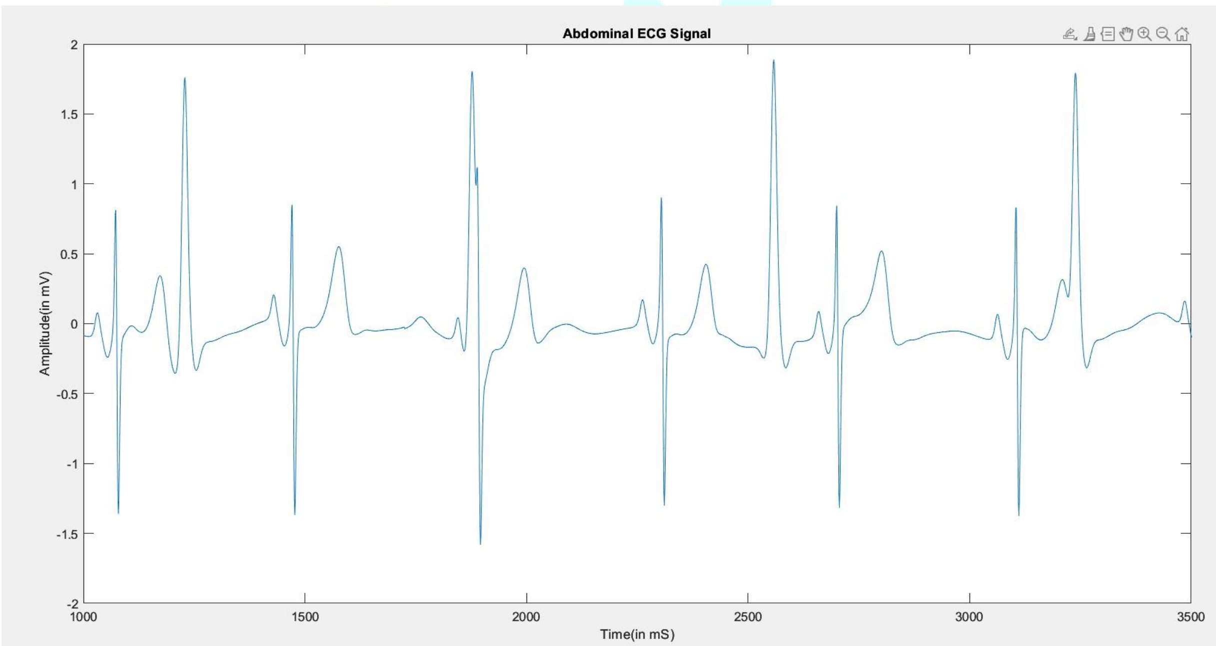
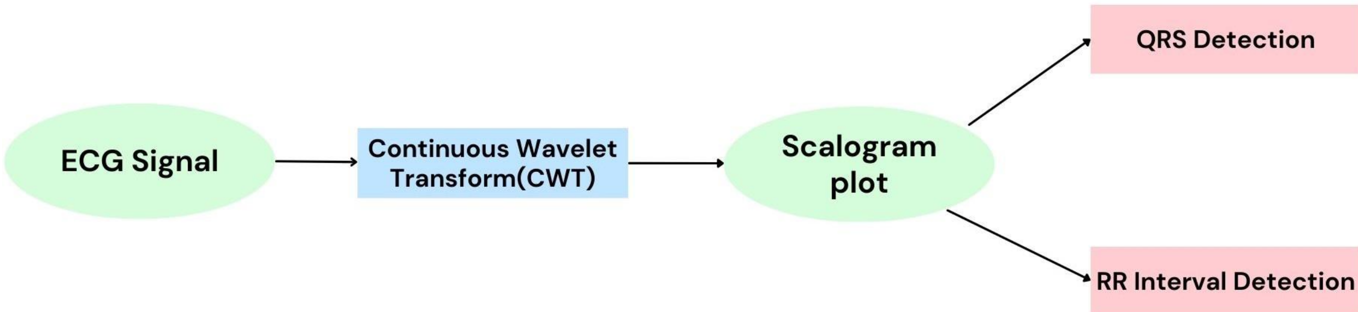


Fig.5: Synthetic Abdominal ECG Signal for a duration of 2500mS(2.5 secs)

II. Algorithm

The scientific methodology employed in this research is demonstrated through theutilization of the following algorithm:



Results & Discussions:

In this section, we are interested to detect the R peak and measure the RR. In order to make agood characterization and fair comparison, different wavelets were used:

a) Morse wavelet:

The Morse wavelet is known for its flexible shape, which can be adjusted by two parameters: bandwidth and frequency peak. This wavelet provides good time-frequencylocalization, allowing analysis of both high and low-frequency components in the ECG signal. It has excellent concentration properties in both time and frequency domains,

making it suitable for detecting and characterizing various waveforms in the ECG signal, including QRS complexes, P-waves, and T-waves.

b) Bump wavelet:

The Bump wavelet, also known as the Gaussian derivative wavelet, is characterized by its smooth and bell-shaped form. It possesses excellent frequency localization, making it effective for capturing narrowband frequency components in ECG signals. Bump wavelets are useful for identifying ECG features such as QRS complexes and other oscillatory patterns with well-defined frequency content. However, its time localization is relatively poorer compared to the Amor and Morse wavelets.

c) Amor wavelet:

The Amor wavelet is characterized by its compact support and symmetric shape. It has ahigher time resolution, making it well-suited for analyzing sharp and transient features inECG signals. The Amor wavelet offers good time localization but sacrifices frequency localization to some extent. Due to its shape, it can effectively capture QRS complexes, P-waves, and other sharp waveform components of the ECG signal. However, it may notbe as efficient in capturing lower-frequency components.

I. Why are these wavelets used in the scalogram analysis of ECG signals?

Scalogram analysis involves decomposing a signal into different frequency components overtime, providing a time-frequency representation of the signal. In the context of ECG analysis, scalograms help visualize the dynamic changes in the frequency content of the ECG signal,
enabling the identification and analysis of specific waveform components.

Amor, Morse, and Bump wavelets are used in scalogram analysis of ECG signals due to theirspecific properties and advantages:

1. ***Localization:*** These wavelets offer different degrees of time and frequency localization, allowing precise identification and analysis of various ECG features like QRS complexes, P-waves, and T-waves. The choice of wavelet depends on the specificfeatures of interest and the trade-off between time and frequency localization.

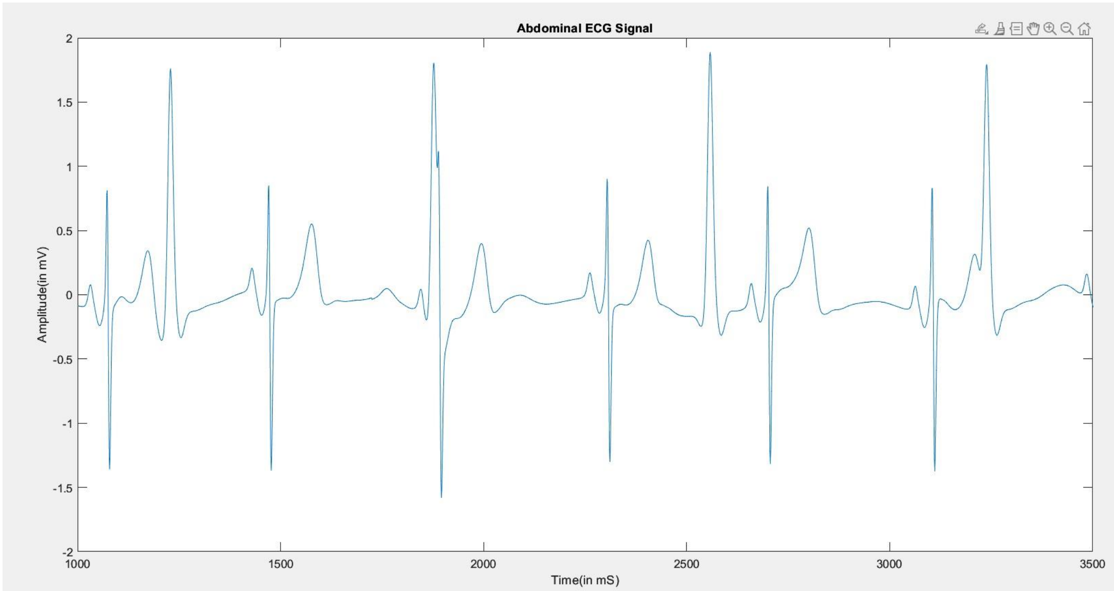
2. ***Frequency selectivity:*** ECG signals often contain components with different frequencycharacteristics. By selecting wavelets with appropriate frequency responses, such as the Bump wavelet for narrowband features or the Morse wavelet for a broader frequency range, the scalogram analysis can highlight and separate these components.

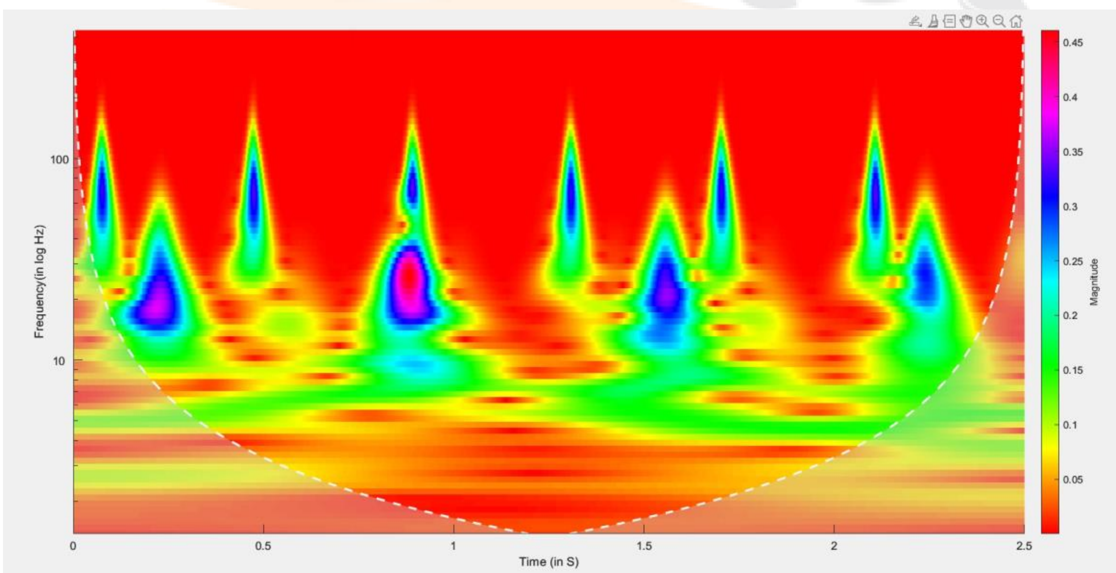
3. ***Adaptability:*** The Morse wavelet's adjustable parameters provide flexibility to adapt todifferent frequency content and scale of ECG signals. This adaptability enables capturingboth high and low-frequency components accurately.

II. Results:

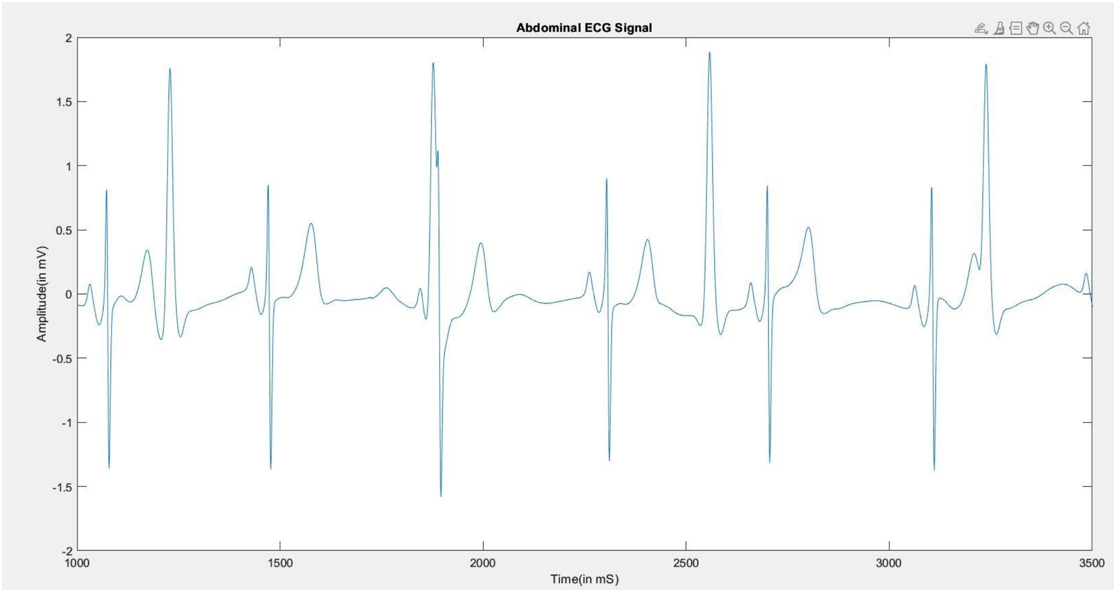
The results of the scalogram analysis for above mentioned wavelets are as follows:

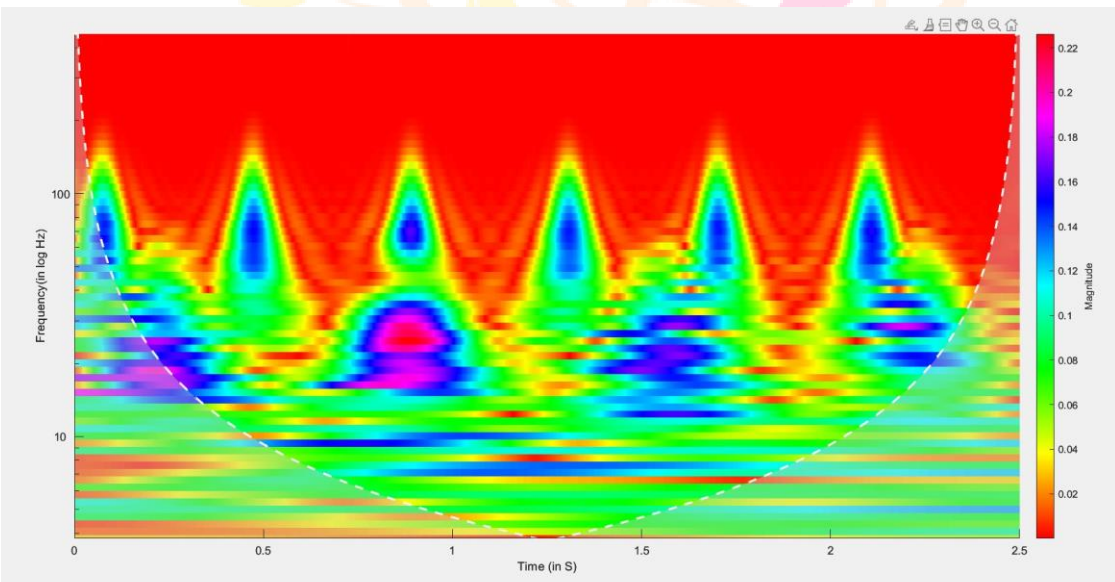
a) Morse Wavelet:



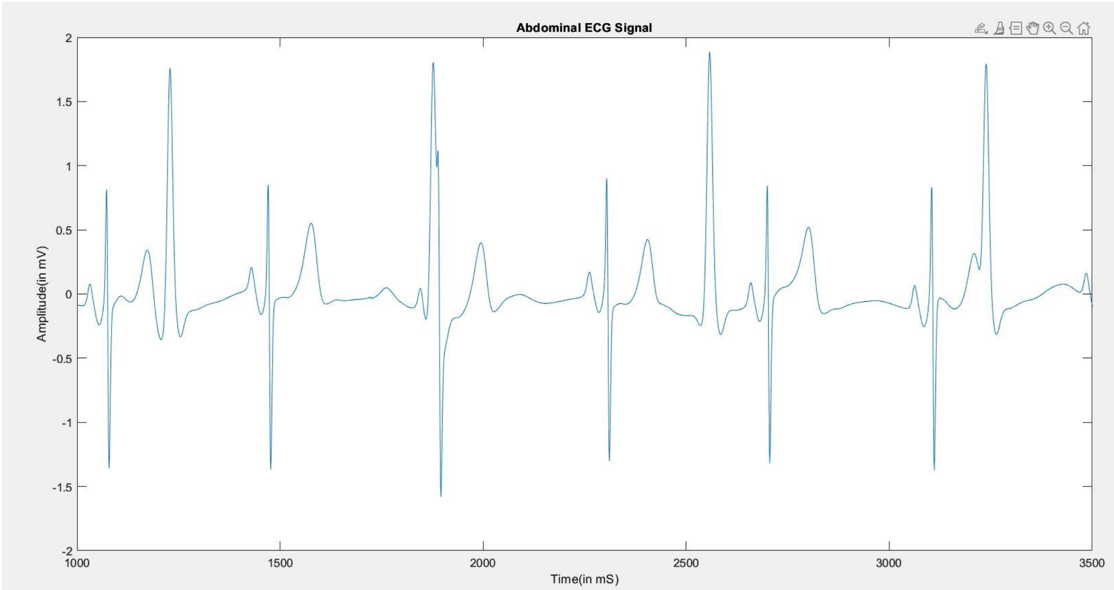


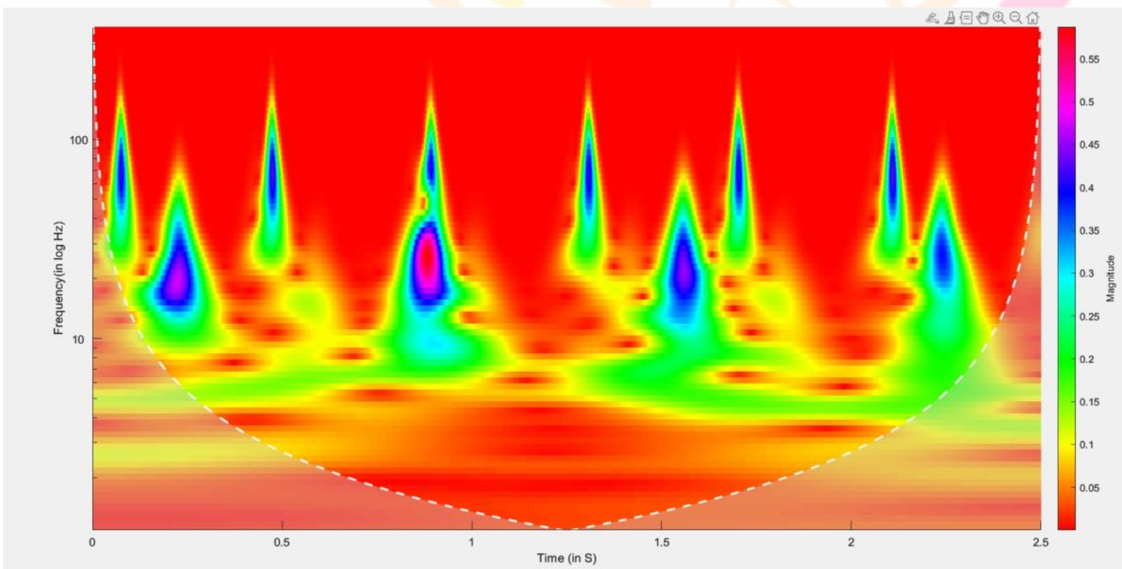
b) Bump Wavelet:





c) Amor wavelet:





III. Discussion:

For the performance evaluation of these wavelets, let's divide them into the followingcategories:

a) Time-Frequency Localization:

The Morse wavelet offers an excellent concentration in both the time andfrequency domains, providing precise time-frequency localization. It can
accurately capture different frequency components of the ECG signal, includingboth high and low-frequency features. This wavelet particularly plays an important role in detecting and characterizing various waveform components inthe abdominal ECG signal.
The Bump wavelet, with its smooth and bell-shaped form, is adept at capturing narrowband frequency components. However, its time localization may not be asgood as the other two wavelets.
The Amor wavelet has good time localization, making it suitable for capturingsharp and transient features in the ECG signal. This can be beneficial for identifying abrupt changes and fast waveforms present in the abdominal ECG.

b) Frequency Selectivity:

The Morse wavelet offers flexibility in adjusting the bandwidth and frequency peak, allowing it to adapt to different frequency ranges. This makes it a versatilechoice for analyzing a broad range of frequency components present in the
abdominal ECG signal.
The Bump wavelet is known for its frequency localization and can effectivelycapture narrowband features. If the abdominal ECG signal contains specific
oscillatory patterns with well-defined frequency content, the Bump wavelet maybe particularly suitable for highlighting these components.
The Amor wavelet, while providing good time localization, may sacrifice some frequency selectivity compared to the other two wavelets. It might be better suitedfor capturing higher frequency features rather than narrowband components.

Conclusion:

In conclusion, based on the comparative analysis of wavelets for Continuous Wavelet Transform (CWT) scalogram analysis of abdominal ECG signals, the Morse wavelet emerges as a strong
contender among the Amor and Bump wavelets. The Morse wavelet offers several advantagesthat make it well-suited for this specific application.

Firstly, the Morse wavelet exhibits excellent time-frequency localization, allowing for precise identification and analysis of different waveform components in the abdominal ECG signals. Itsconcentration properties in both the time and frequency domains enable accurate detection and
characterization of various features, including QRS complexes, P-waves, and T-waves. This levelof detail is crucial in accurately assessing the dynamics of abdominal ECG signals.

Secondly, the Morse wavelet provides adaptability through adjustable parameters, such as bandwidth and frequency peak. This adaptability allows it to effectively capture a broad range offrequency components present in abdominal ECG signals. As a result, it can accommodate both high and low-frequency features, making it a versatile choice for comprehensive analysis.

Additionally, the Morse wavelet offers excellent frequency selectivity, ensuring that narrowband frequency components in the abdominal ECG signals are appropriately captured. This characteristic is particularly advantageous when analyzing specific oscillatory patterns or identifying certain frequency-specific phenomena in the signal.

While both the Amor and Bump wavelets have their own strengths, such as good time localization and frequency selectivity, respectively, the Morse wavelet outperforms them in termsof its combined advantages. Its ability to simultaneously provide high-quality time-frequency localization, adaptability, and frequency selectivity positions it as a superior choice for CWT scalogram analysis of abdominal ECG signals.

By utilizing the Morse wavelet in future studies, researchers and clinicians can expect improved accuracy and comprehensive insights into the dynamic characteristics of abdominal ECG signals. This can lead to enhanced diagnostic capabilities, a better understanding of physiological phenomena, and potentially improved patient care in the field of abdominal ECG analysis.

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