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Denoising of ECG Signal Using SWT and FDM

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ABSTRACT
Cardiovascular disorders are identified using electrocardiogram (ECG) data. Various sounds, such as power line interference, baseline wandering, motion artifacts, and electromyogram noise, damage the electrocardiogram (ECG) data during signal acquisition. It can be challenging to eliminate these sounds from the recorded ECG signal since an ECG signal is non-stationary. Creating an automated ECG denoising pipeline that can be applied to extensive ECG data analysis. To address the absence of translation-invariance, the wavelet transform method known as the Stationary Wavelet Transform (SWT) was developed. To obtain this Stationary Wavelet Transform and denoise the ECG data using it, a Python or Octave code might be built. As a result, it gets rid of these sounds without losing the characteristics of the ECG signal. Our ability to measure diagnostic parameters including heart rate, QT interval, and ST segment deviation will be improved as a result.

Keywords—**DataSet, ECG, SWT, FDM, and Python Code**

I.I NTRODUCTION

Many different types of filters can be employed to denoise this ECG signal. Highpass filters, lowpassfilters, notch filters, adaptive filters, Empirical Mode Decomposition (EMD), wavelet transform (DWT, SWT), blind source separation method, and Fourier decomposition method (FDM) are a few examples. These methods successfully eliminate noise while preserving the signal's important characteristics. SWT oneof the finest ways for non-stationary signals in real-time applications among all the methods discussed above. The Stationary Wavelet Transform (SWT) is a wavelet transform technique designed to overcome the discrete wavelet transform's (DWT) lack of translation invariance.Heart attacks, heart failure, and stroke are just a few of the different heart or blood vessel issues that are referred to as cardiovascular disease (CVDs). The conduction system of heart regulates the production and transmission of electrical signals that drive the heart to contract and pump blood. By affixing electrodes to precise locations on the human body, this electrical activity can be detected. A composite recording of the electrical activity detected by electrodes takes the form of the well- known ECG Graph.

I.I ECG Uses

ECG is a most well-known tool for a variety of biomedical tasks, including heart rate monitoring, studying arrhythmia, and identifying anomalies in the heart, identifying emotions, and biometric identification. An ECG signal needs to be clear for proper diagnosis of heart problems.

I.II Sounds

An ECG signal needs to be clear in order to diagnose heart problems properly. Most of the time, noise and artifacts taint the ECG signals, making them unclean. The main causes of noise are insufficient skin contact between electrodes and skin, electrode placement that isn't ideal, body movements caused by different muscles, breathing, nearby electrical equipment, and electronic gadgets used by the system itself. So that ECG features can be properly and effectively evaluated, sounds and artifacts must be eliminated.
The following is a list of typical noises.

1. **Baseline wandering:** This low-frequency noise, which typically ranges between 0.15 and 0.3 Hz, isbrought on by the patient's

breathing or movement.

2. **Powerline interference:** This high-frequency noise, which typically originates from the power supply lines, occurs in the frequency range of 50 Hz to 60 Hz.

3. **Motion artifacts:** These low-frequency noises are caused by the movement of the subject and thedisplacement of the skin-contact electrodes.

4 **Muscle-produced electromyogram noise:** This commonly occurs in the frequency range of 5 to 500Hz and caused by muscles other than cardiac muscles contracting and relaxing.

II.LITERATURE SURVEY

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III. METHODOLOGY

Signals from electrocardiography (ECG) are frequently used to detect problems in the heart and keep track of heart health. However, a variety of noise, such as baseline, muscle artifacts, power line interference, and electrode motion artifacts, frequently ECG readings. It might become difficult to effectively identify and analyze the underlying heart activity when noise reduces quality of ECG readings. The efficient denoising of ECG data using the stationary wavelet transform (SWT) technique is the issue this study attempts to solve.

III.I ECG denoising working model for SWT:

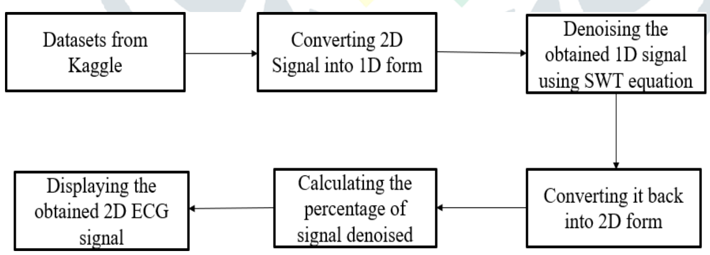


Fig. 1 shows the ECG denoising working model.

The stages listed below are used in SWT for ECG denoising:

Step 1: One-dimensional wavelet decomposition of a signal. Wavelet transformation used to do a multi-resolution analysis ona noisy signal, which entails picking the appropriate wavelet and performing an N-layered wavelet decomposition to the data.

Step 2: At this step, a threshold is applied to the wavelet decomposed sub-bands. The threshold used to minimize orget rid of the noise that is present in sub-bands.

Step 3: Wavelet reconstruction in single dimension. The denoised ECG signal is reassembled in this step using theThresholder sub-bands. The output is an ECG has been denoised.

The block diagram for the process of denoising the ECG is shown in the above image. Signal is always displayed in one dimension (1-D). As a result, signal is assessed in two dimensions (2-D) to learn more about the relationships between time and frequency coefficients. A denoising method is based on stationary wavelet modification can greatly increase the signal-to-noise ratio. A Stationary

Wavelet Transform algorithm can developed to generate the denoised ECG data, which can used further diagnosing any heart issues. Order to compare the algorithm's performance, some input and output parameters are computed and compared. Order to find SNR values, the input and output signals are compared to one another. The ratio between the signal and noise powers is calculated and expressed as a percentage. The SWT algorithm used to compare the denoised signal's various properties, allowing for a discussion accuracy of denoising algorithms.

III.II ECG denoising working model for FDM

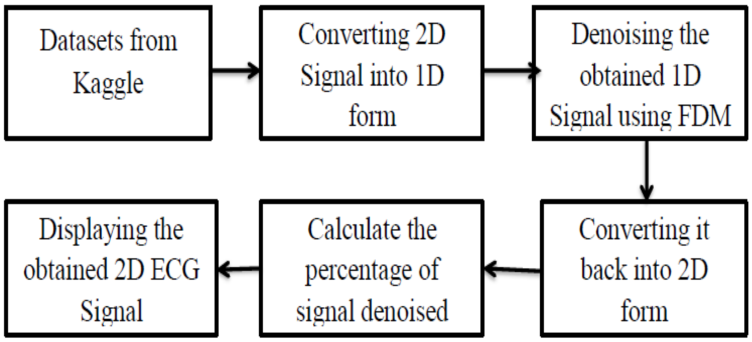


Fig.2 shows the ECG denoising working model using FDM

The following steps would normally be included in an FDM for ECG denoising:

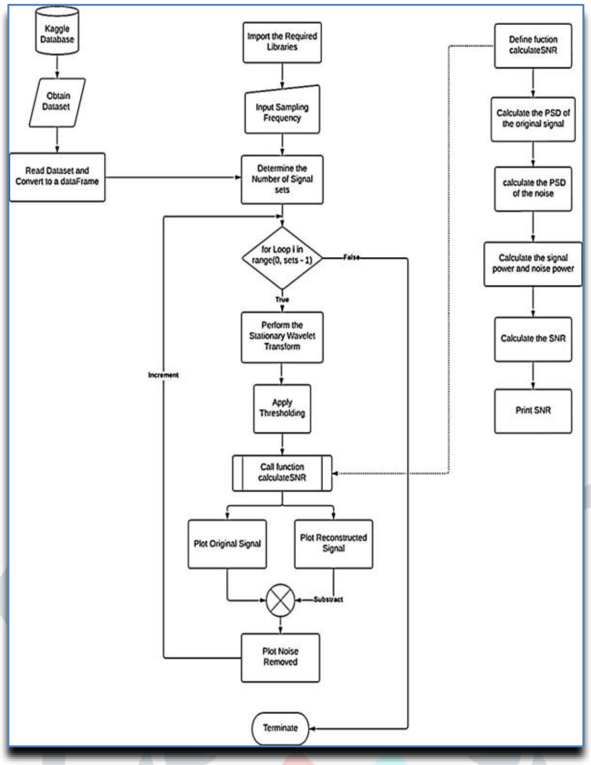
Step 1: Signal Fourier decomposition in one dimension. FDM is used to do multi-resolution analysis on the noisy signal,which entails picking the appropriate wavelet and performing an N-layered wavelet decomposition to the signal.

Step 2: At this point, a threshold is applied to the fourier decomposed sub-bands. The threshold used to minimize orget rid of the noise that is present in sub-bands.

Step 3: Wavelet reconstruction in single dimension. The denoised ECG signal is reassembled in this step using theThresholder sub-bands. Result is an ECG has been denoised.

The block diagram for the process of denoising ECG is shown in above image. The signal is always displayed in one dimension (1-D). As a result, the signal is assessed in two dimensions (2- D) to learn more about the relationships between time and frequency coefficients. A Fourier decomposition modification-based denoising technique can dramatically increase the signal-to-noise ratio. A Fourierdecomposition algorithm can be developed to generate the denoised ECG signal, which is useful for further diagnosing any heart issues. In order to compare algorithm's performance, some input and output parameters are computed and compared. In order to calculate the SNR values, the input and output signals are compared to one another. The ratio between the signal and noise powers is calculated and expressed asa percentage. The FDM algorithm is used compare denoised signal's various properties in order to examine the accuracy of denoising approaches.

IV. FLOW CHART AND IMPLEMENTATION



IV.I ANALYSIS for SWT:

1.Import the necessary libraries for ANALYSIS for SWT, including'matplotlib.pyplot', 'pandas','numpy', 'pywt','math', and'scipy.signal'.
2. Create a function to calculate SNR given an input array called calculateSNR(arr, axis=0, ddof=0).
3. Using 'pd.read_csv' to read data from CSV file and storing it in a DataFrame.
4. Based on quantity of samples in data, define the sampling frequency ('fs') and the time axis('timeAxis').
5. Go through each signal in dataset iteratively:
6. Choose the wavelet parameters for the wavelet type,order,level, and threshold ('waveletChoose', 'levelChoose,' and'setThreshold').
7. Take the signal information out of DataFrame.
8. Using 'pywt.dwt' or 'pywt.wavedec', depending on level selected, apply the wavelet transformto the signal.
9. Use 'pywt.Wavelet' to declare the wavelet.10. To separate ap
the coefficients.
11. Use "sp.welch" from "scipy.signal" to compute the power spectral density (PSD) and noise.
12. Add the PSD values together to calculate the signal power, and the PSD values together tocalculate the noise power.
13. Determine the signal-to-noise ratio (SNR) using the "calculateSNR" function using theequation: "SNR = 20 * log10(signalPower / noisePower).
14. Use the 'plt.plot' command to plot original and reconstructed signals in the first subplot..15. After the loop, print value of 'nSamples' (the number of samples).

IV.II ANALYSIS for FDM:

1. Fourier Transform: Using np.fft.fft(), the function get_fourier_coefficients(signal) performs a FastFourier Transform (FFT) on the input signal. The Fourier coefficients are returned.
2. Noise Removal: By thresholding the Fourier coefficients, the function remove_noise(coefficients,snr_threshold) removes noise from the signal. It accepts two inputs: the SNR threshold snr_threshold and the Fourier coefficients coefficients. The noise threshold is determined by making a duplicate of the coefficients and dividing their highest absolute value by a formula derived from the SNR threshold. Coefficients below the noise threshold are then set to 0. Returned are the cleaned coefficients.
3. The function reconstruct_signal(coefficients) uses np.fft.ifft() to perform the inverse Fourier Transform (IFFT) on the input coefficients. It delivers the signal that was rebuilt.
4. The function calculate_snr(noisy_signal, reconstructed_signal) determines the SNR between the noisy signal and the reconstructed signal. It determines the strength of the noise signal (the differencebetween the original and reconstructed signals) and the strength of the noisy signal (noisy_signal). The ratio of the original power to the noise power multiplied by 10 times the logarithm base 10yields the SNR, which is measured in decibels (Db).
5. Reading Noisy Signal: The code uses the pd.read_csv() function to read the noisy ECG signal data from the CSV file ptbdb_normal.csv. It is assumed that the ECG data is kept in the CSV file's columns. The user is prompted to enter the sample frequency, or fs.

6. Denoising Loop: The program starts an iterative loop, loops through each signal set (row) in the data. It obtains noisy signal for each signal set by taking the row values out of the data. Process of denoising is then carried out:
7. Using the get_fourier_coefficients() function, it determines the Fourier coefficients of the noisy signal.
8. The Fourier coefficients are cleaned up by executing remove_noise() together with the coefficients and an SNR threshold. Which coefficients are set to 0 depends on the threshold.
9. Calling reconstruct_signal() with the cleaned coefficients reconstructs the denoised signal.
10. Using calculate_snr(), it determines the SNR between the noisy original signal and the reconstructedsignal.
11. Using plt.subplot() and plt.plot(), it depicts the noisy signal and the noise that removed in separatesubplots.
12. The plots are then displayed using plt.show(), and the layout is modified using plt.tight_layout().

V.RESULTS AND DISCUSSION

V.I RESULTS for SWT:

The Massachusetts Institute of Technology-Beth Israel Hospital Arrhythmia Database is referred to as MIT-BIH. For study and analysis in the areas of electrocardiography (ECG) and arrhythmia detection, it is an extensively utilized database. In MIT-BIH Arrhythmia Database, each entry is made up of an annotated ECG signal is continuously recorded and typically lasts for many hours. Both the noisy and the denoised versions of ECG are defined in Fig. 3 below. This case, all that required that to convert noisy signal into its denoised version is the Python code that was previously provided.

After this signal has been effectively denoised, the signal power and noise power, or SNR value, are used to calculate the total percentage of denoise. There are numerous patient signal sets, and signal set 1 has an SNR of 50.2387%. This has a signal power of 8.86% and a noise power of 0.03%.

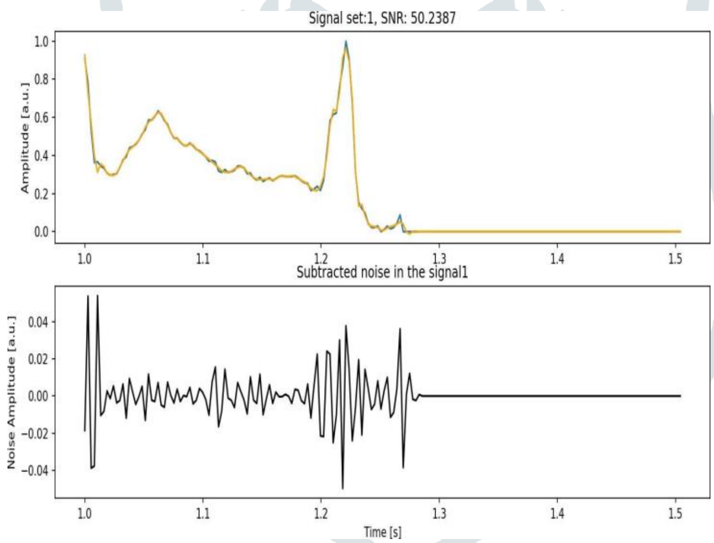


Fig. 3: The erratic and denoised ECG signal from Mitbih

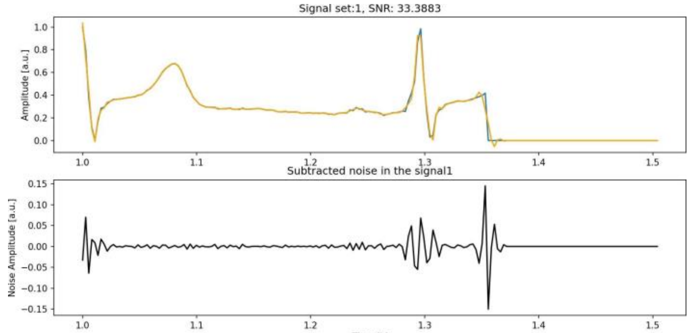


Fig 4. a typical ECG signal is shown with noise and denoising.

Signal from Physikalisch Technische Bundesanstalt DataBase (PTBDB) of a healthy patient is presented in the Fig. 4 above and has been denoised using the SWT technique. Here, the Python code given above is all that is needed to transform noisy signal into its denoised form. The total percentage of denoise is determined using the signal power and noise power, or SNR value, after signal has been denoised. As well known, a strong signal and low noise level indicate an excellent signal with high SNR value.

There are numerous patient signal sets, and signal set 1 has SNR of 33.3883%. This has a signal power of 1.43% and a noise power of 0.02%.

V.II RESULTS for FDM:

Signal from Physikalisch Technische Bundesanstalt DataBase (PTBDB) of a healthy patient is presented in the Fig. 5 below and has been denoised using the FDM technique. Here, the Python code given above is all that is needed to transform noisy signal into its denoised form. The total percentage of denoise is determined using the signal power and noise power, or SNR value, after signal has been denoised. As well known, a strong signal and low noise level indicate an excellent signal with high SNR value.
There are numerous patient signal sets, and signal set 1 has SNR of 8.8021%. This has a signal power of 0.097% and a noise power of 0.012%.

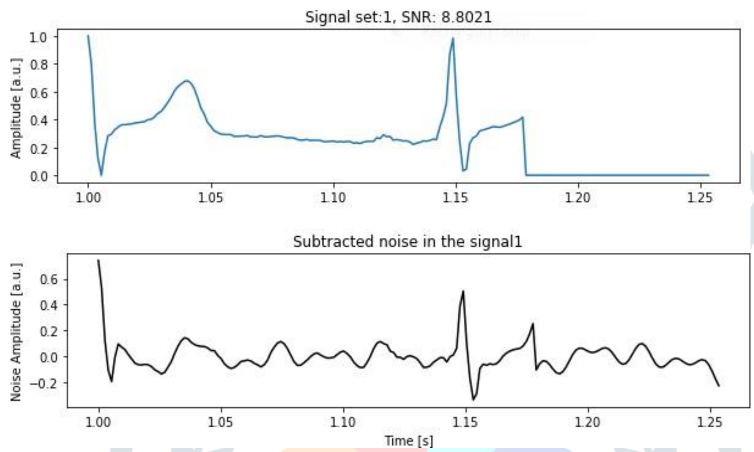


Fig 5. a typical ECG signal is shown with noise and denoising.

CONCLUSION

The stationary wavelet transform is an effective method for denoising ECG signals. It can successfully eliminate noise while keeping ECG signal's crucial characteristics. The WT divides the signal into many frequency bands, enabling the detection and elimination of particular kinds of noise. Original signal is recovered using techniques for thresholding and reconstruction. The wavelet function and decomposition level should be carefully determined depending on the properties of ECG signals and the types of noise present, as these factors can have a significant impact on how well the denoising process performs.

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