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Pre-processing the Photoplethysmography Signals for Enhancing the Cardiovascular Diseases Detection for Wrist Pulse Analysis in Nadi Ayurveda

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Abstract

INTRODUCTION: In recent years, Photoplethysmography (PPG) signal has played a vital role in detecting Cardiovascular Diseases (CVDs) in case of wrist pulse analysis emulating the Nadi Ayurveda. The PPG signals acquired from the sensor measurement are severely distorted by various artifacts, which significantly impact the accuracy of disease detection and hamper the disease diagnosis process.
OBJECTIVES: Removing the noises is essential before detecting CVDs from the signals and thus, developing a simple and effective noise reduction method for enhancing the PPG signal quality constitutes a challenging research problem, particularly with prominent artifacts.
METHODS: This paper designs an effective pre-processing technique that improves denoising methods to enhance the PPG signal quality. The design of pre-processing technique contains two major phases: Primary denoising-based artifact removal and secondary denoising-based Premature Ventricular Contraction (PVC) detection and Power-Line Interference (PLI) noise removal. The primary denoising method involves coarse and fine-grained filtering. The coarse-grained filtering removes the major artifacts, such as Baseline Wander (BLW) and Motion Artifacts (MA), by developing the Two-Stage Adaptive Noise Canceller (TANC) method. The fine-grained filtering process utilizes a detrended filter to filter the refined signal obtained from the TANC method. For the signals filtered from the primary denoising method, the secondary denoising method targets to detect the PVC-induced PPG signals from the decomposed high-frequency signals and removes high-frequency noise, such as PLI from noisy signals, by adopting the Wavelet Transform (WT) method.
RESULTS: During the signal reconstruction process in the WT method, the research work reconstructs the denoised PPG signals along with the PVC-induced PPG signals. The experimental results of the noise removal methodology illustrated significant improvements in PPG signal quality.
CONCLUSION: The designed pre-processing technique effectively denoises PPG signals, leading to enhanced signal quality which can further aid in accurate disease detection.

Keywords: Photoplethysmography Signal, Primary Denoising, Secondary Denoising, Two-stage Adaptive Noise Cancellation, Detrended Filter, Wavelet Transform, and Premature ventricular contraction, Nadi Ayurveda

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1. Introduction

Cardiovascular Diseases (CVDs) are non-communicable disorders, and their mortality rate is about 50% among non-communicable disorders [1]. According to the World Health Organization (WHO), around 17.9 million deaths are reported annually and 32% of all deaths globally [2]. As the global burden of CVDs increases [3] with its alarming prevalence among the world population and lead CVDs as the main cause of death. To predict CVD and recognize its health condition, non-invasive arterial pulse wave analysis is a suitable and efficient method to assist in detecting cardiovascular

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disorders. A pressure wave produced due to the periodic cardiac contraction is a pulse wave that is utilized for the non-invasive computation of the cardiovascular parameters, namely Cardiac Output (CO), Stroke Volume (SV), Blood Flow Alternate, Total Peripheral Resistance (TPR), and more. The pulse wave is divided into two major types: photoplethysmography (PPG) and radial pulse wave. Both are broadly utilized for the estimation of cardiovascular function [4]. The waveform pre-processing is applied to decrease the interference components and remove the respiration and motion artifacts produced while obtaining pulse waves. The waveform pre-processing also interprets the morphology of pulse waves and helps to acquire duplicity-free and stable pulse waves. It is envisioned that the PPG pulse wave is one of the prominent technologies and non-invasive techniques beneficial in the clinical aspect of estimating many physiological characteristics. The clinical sensor measurements for acquiring PPG signals are susceptible to various noises. The information from PPG signals is crucial for assisting cardiovascular disease diagnosis. Still, such signals are contaminated with different noises, such as Power Line Interference (PLI) noise, Motion Artifact (MA), Low Amplitude PPG signal, Baseline Wander (BLW) noise, and others [5]. These noises corrupt the PPG signals and cause inaccurate PPG interpretation, leading to false detection of CVDs. Thus, pre-processing the raw PPG signal becomes necessary for CVDs detection to provide proper diagnosis and prevent inaccurate PPG waveform. More recently, Cardiology is one of the main applicative fields of PPG pulse waves that are exploited for diagnosing, monitoring, and screening CVDs [6].

PPG Signal specifications: Normal pulse wave frequency ranges from 0.5 Hz to 5 Hz, but the PPG signals are contaminated as the high-frequency range is around 20 Hz. The PPG signal is often accompanied by high-frequency noise elements, which are to be removed by a low-pass filter process with a 5Hz cut-off frequency. Noise covers a different range of frequencies. Baseline drift noise caused by respiration activity, the range of the frequency is 0.15–0.3 Hz, but the normal respiratory rate range is about 0.04–1.6 Hz, and the range of motion artifact is 0.1 Hz. Figure 1 illustrates the frequency range of the PPG signals at different stages.

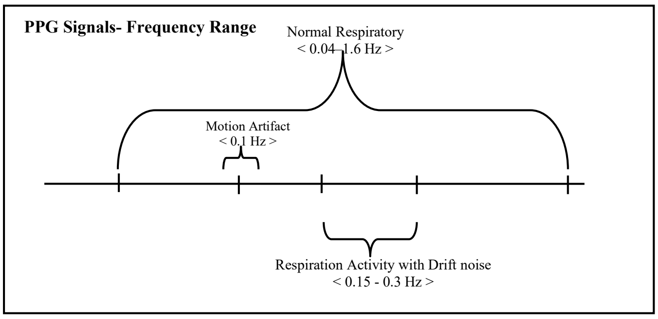


Figure 1. PPG Frequency Range

Figure 2 illustrates the different denoising methods [5] used to remove multiple noises in the PPG signal.

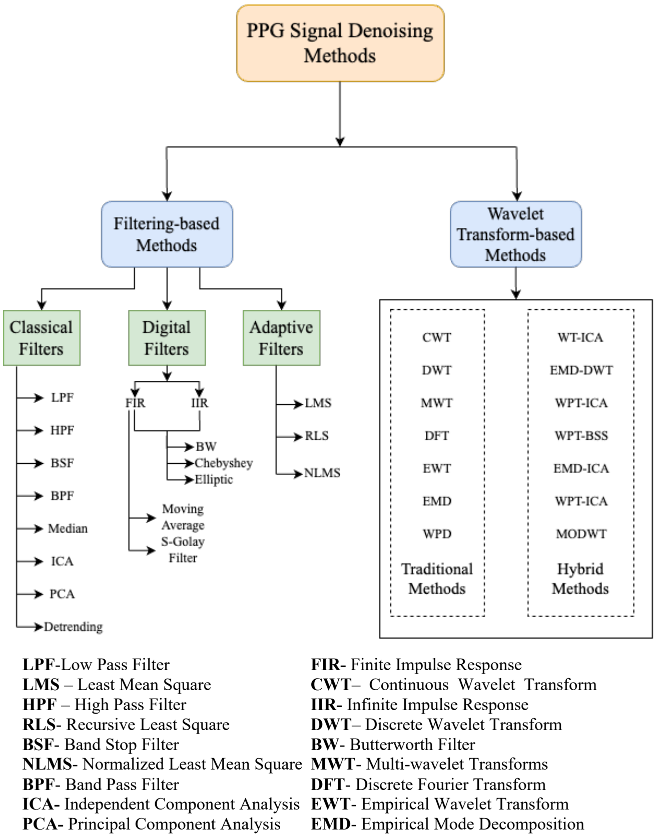


Figure 2. Different Denoising Methods

The paper aims to develop a pre-processing technique for improving PPG signal quality. It mainly focuses on enhancing the PPG signals with rich cardiac-related information, which facilitates the accurate estimation of CVDs. The contributions of the pre-processing methodology are stated as follows.

- The proposed pre-processing technique enhances the accuracy of cardiovascular disease detection by designing two major phases: primary denoising for BLW and MA artifacts removal and secondary denoising for PVC-retained PLI noise removal.
- The primary denoising method involves a coarse-grained filtering process for BLW and MA removal and a fine-grained process for refined signal filtering.
- The secondary denoising method removes PLI from the signals filtered from the primary denoising method, which detects the PVC-induced PPG signals and eliminates the high-frequency PLI noise by the wavelet-based decomposed high-frequency signals.
- Moreover, detecting PVC-induced PPG signals in the wavelet-based decomposed high-frequency PPG signals and retaining the PVC-induced PPG signals during the denoised signal reconstruction process in the WT method facilitated the accurate detection of cardiac vascular diseases.

1.1. Paper Organization

The remainder of this paper is organized as follows. The second section concerns related works on denoising methods for eliminating various noises in raw PPG signals. The proposed pre-processing with various denoising methods is explained in the third section. Experiment and performance analysis are discussed in the fourth section, and finally, the fifth section concludes this paper.

2. Related Work

In PPG-based heart rate algorithm enhancement [7], the 2nd Order Butterworth (IIR) bandpass filtering approach is applied for denoising PPG signals. A Savitzky-Golay filter is employed for high-end noise reduction and smoothening. Finite Impulse Filtering (FIR) is also applied to eliminate unwanted noise from PPG signals for heart rate analysis. A better digital filtering technique [8] employs Gaussian and hamming filters to eliminate noise in the high-frequency range from PPG signals, and proven Gaussian filters deliver better results based on signal-to-noise ratio and error percentage. In PPG scheming system [9], Butterworth-type FIR low pass filter is utilized to get rid of unwanted noise, high-frequency clipping, and motion artifacts. A VLSI wavelet transform-based denoising method was developed that eliminates power-line interference, and this method employs a three-level wavelet decomposition-reconstruction tree and thresholding [10].

An expulsion of baseline drift in PPG signals using a median filter approach [11] at two stage levels was developed and achieved more effective performance than the moving average filter. For the correction of baseline wandering noise in PPG signals, FPGA based 16-bit morphological filtering method [12] was applied, and it highly improved the signal-to-error ratio. This method also suppresses the high-frequency noise using the 10^{th}-order FIR low pass filter. An Aligning Minimum of Alternating Random Signal (AMARS) filter-based approach [13] was proposed to remove baseline drifting in ear and finger PPG signals. This new filtering approach eliminates baseline wandering sequence and morphological changes in PPG with the help of frequency-selective filters. In estimating heart rate [14] from PPG, the baseline wandering noise is removed more effectively using wavelet decomposition from fingertip PPG.

A signal processing method employs comb filter-based wavelet denoising to suppress the motion artifact in PPG as a pre-processing stage [15]. A least square-based noise removal method [16] with adaptive filtering was proposed to eliminate the periodic motion artifacts, and a genetic algorithm [17] using second-order generalized integrators (SOGI) with a frequency-locked loop (FLL) has been developed. Motion artifacts are also detected and eliminated by exploiting statistical analysis and adaptive filtering on PPG signals [18]. A robust heart rate estimation approach [19] was introduced. This approach utilizes adaptive filtering to eliminate the extreme noise caused by the motion artifacts in PPG.

3. The Proposed Pre-processing Methodology

3.1. Preliminaries

PPG signals are collected at the human body's terminus using a PPG sensor, such as fingers, toes, and earlobes. Various PPG devices acquire PPG signals based on the type of sensors used, the location of the device, and the method of transmission of the collected data. The location of the PPG sensor is one of the core factors for recording appropriate and quality cardiac signals. The finger sensor records high amplitude signals compared to the PPG recordings from other human body locations.

Sensor Measurements: PPG signal is constructed by either transmission or reflection form using tissue contact sensing [20]. Light-Emitting Diodes (LED) are mostly utilized light sources that employ the detectors such as phototransistors, silicon photodiodes, and photocells. A sensor comprises an array of LEDs and a photodiode that defines the probe configuration and measurement. The photodiode and LED are seated on opposite sides of a clip in transmission probes, and the light transmitted from the LED travel through the tissue to the photodiode. Transmission probes are the most broadly utilized in healthcare systems for measuring arterial oxygen saturation. Reflection probes are virtually utilized for vascular tissue sites owing to their seating between LED and photodiode and are utilized in consumer wearable devices.

Flexible Sensors and Configurations: With the consistent progress of electronics and sensor technology, quick advancements have led to the development of flexible sensors, such as the graphene-based sensor. The main properties of flexible sensors are high flexibility, lightweight, cost-effective, simple processing, and utilized to measure fragile physiological signals. The instrumentation and sensor setup are essential to decide the quality of the generated signal. PPG signals with high-quality and less noise are obtained using the optimal PPG instrumentation. The sensor design should also be optimized to ascertain the appearance and quality of the PPG waveform [8]. The sensor configuration decides the criteria depending on the application's intention.

3.2. The Phases of the Proposed Method

The proposed work focuses on enhancing the acquired PPG signals to extract the potentially rich cardiac-related information and consequently improve CVDs detection performance. Furthermore, it is necessary to improve the quality of PPG signals via pre-processing, which helps accentuate the desired PPG waves for its analysis. To eradicate the noises, present in the raw PPG signal during the process of PPG signal acquisition, this work presents an effective pre-processing technique that is an improved denoising scheme involving primary denoising and secondary denoising, as illustrated in Figure 3.

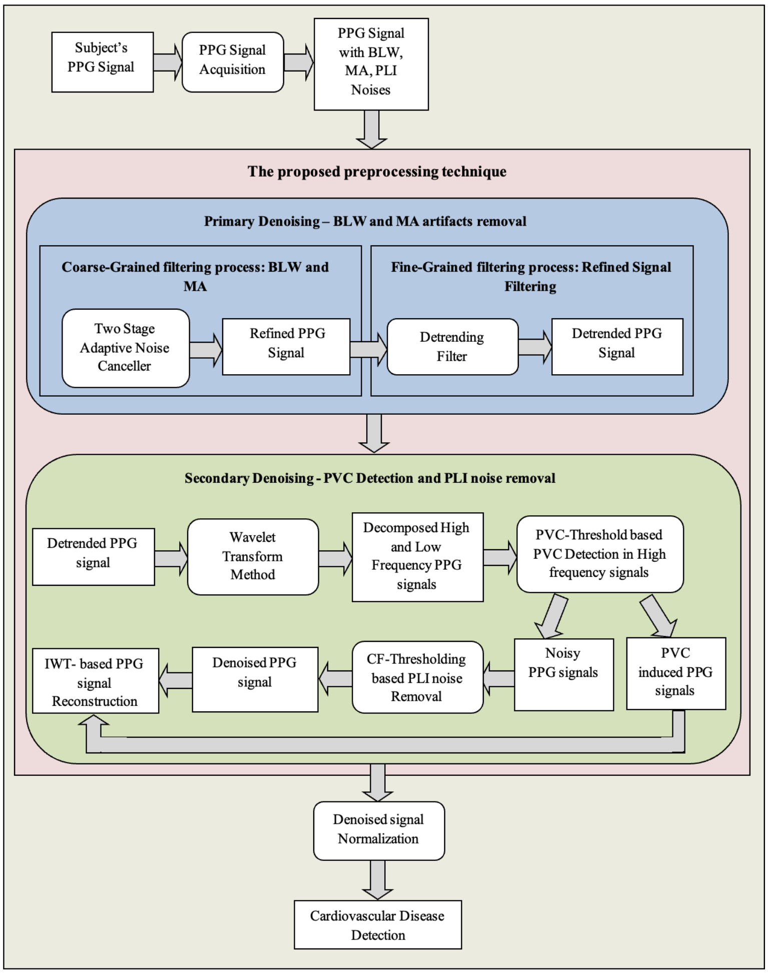


Figure 3: An Outline of the proposed pre-processing technique for cardiovascular disease detection

3.2.1 Primary Denoising – BLW and MA artifacts removal

Initially, it concentrates on eliminating the major artifacts, such as BLW and MA, accumulated in the acquired PPG signals. BLW is low-frequency noise, referred to as the gradual alteration of signal baseline necessary for heart analysis. Inaccurate heart rate estimation is obtained while an iso-electric line of PPG is influenced by the BLW due to the temperature fluctuations in the environment, breathing movements, and biasing in an instrumentation amplifier. Motion noise impact on the PPG waveform also occurred due to sudden breathing changes and sensor displacement. Several techniques have been introduced to minimize these noises for collecting high-quality signals. Robust algorithms are developed by signal processing methods to reduce the impact of MA on PPG measurements. Although, the elimination of movement artifacts is very challenging, especially noise identical to normal physiological variation. In essence, it is essential to maintain high signal quality in applications demanding the pulse shape for morphological interpretation. Primary denoising method is proposed, which involves a coarse-grained filtering process to eliminate the BLW and MA artifacts in PPG signals and a fine-grained filtering process to remove further noises and filter the refined signal.

(i) Coarse-Grained filtering process for BLW and MA Removal:

In this filtering process, the proposed work designs the Two-stage Adaptive Noise Canceller (TANC) method from the inspiration of the research work [19] to eliminate the BLW and MA noises in the PPG signals. Adaptive Noise Cancellation (ANC) represents a common denoising method that employs adaptive filters for evaluating signals affected by noise or interference. Researchers [19], [21] proposed the cascaded adaptive noise canceller by utilizing different adaptive filters for removing the multiple artifacts acquired in the PPG signals. Due to the existence of multiple artifacts, the deduction of the noise reference signal from the primary input becomes highly sensitive to selection which causes difficulty in removing the respective artifacts and deteriorating cardiac-related information during reference signal selection from the primary input PPG signals. It also increases the computational complexity by adopting different adaptive filters in the denoising method. To subjugate this drawback, this work designs the TANC method for major noise removal and exploits the LMS algorithm to filter noise-free PPG signals from noisy signals. It generates the noise reference signal by deducting the two-channel PPG signals. The proposed TANC method for removing BLW and MA from the raw PPG signal is depicted in Figure 4.

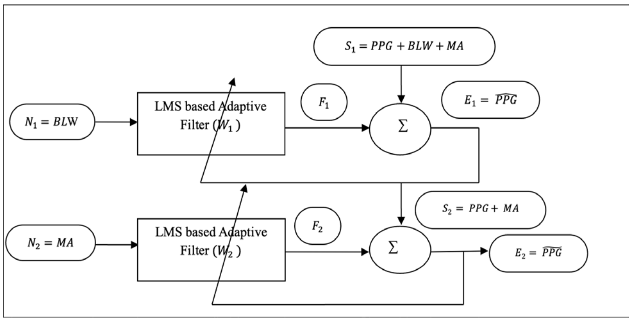


Figure 4. Proposed Two-Stage Adaptive Noise Canceller

Initially, an approximate reference signal consisting of BLW and MA is generated through adaptively filtered and deducted from the primary input as raw PPG signals. Then, the PPG signaled with accumulative noise and generated reference signals are provided as the primary input to the TANC system. Initially, the adaptive noise canceller obtained the partially corrected BLW noise-free PPG signal. Based on the LMS algorithm, the noisy signals correlate only with the noise in the PPG signals with accumulative noise, then lately subtract the respective noisy signals and deliver artifacts-free PPG signals.
From the above Figure 4, $S_1$is the primary input (desired signal corrupted with undesired noise) passed to the first component (adaptive noise canceller), which comprises undesired artifacts such as BLW and MA.N_1 forms the secondary or reference input from the first component, N_1contains the reference BLW, and it is associated only with the BLW present in the distorted PPG signal S_1, N_2 indicates the reference input of the second component, and N_2encompasses the reference motion artifacts that are correlated only with the motion artifacts present in the corrupted PPG signal S_1.F_1andF_2 are the respective adaptive filter outputs and E_1denotes the partially corrupted PPG signal free from BLW ($\widehat{PPG}$) act as the primary input S_2 to the second component, whereas E_2 denotes the filtered PPG signal ($\widehat{PPG}$) free from BLW and MA. W_1 and W_2 are the adaptive filter coefficients of the respective LMS in the adaptive noise canceller components. Such coefficients are computed based on the weight update equation,

$$W_i = W_{i-1} + \mu N_i^T E_i \qquad (1)$$

ii) Fine-Grained filtering process for Refined Signal Filtering:

After TANC-based artifacts removal from the raw PPG signals, the proposed methodology considers the generated artifacts-free PPG signal ($\widetilde{\text{PPG}}$) as a refined signal, and subsequently, it applies a detrending filter to the refined PPG signals ($\widetilde{\text{PPG}}$) to reduce the non-stationary trends of the PPG signals. For better signal analysis, the Detrending filter diminishes unwanted long-running trends and non-stationary components from the PPG signals. The non-stationary trends in PPG signals cause difficulties in PPG pattern analysis. Hence, it is significant to eliminate the non-stationary trends in the PPG signal for effective CVD disease detection. It is assumed that the trend is smooth and contains Y with the property additive convexity observed on the signal at every point, and must be as small as possible, computed by equation (2).

$$\hat{Y}_{trend} = argmin^{Y} \left\| Y - \hat{Y} \right\|_2^2 + \left\| D_2 \hat{Y} \right\|_2^2 (2)$$

Where Y is the refined ($\widehat{PPG}$) signal obtained from the TANC-based denoised technique, $\hat{Y}_{trend}$is the determined trend in Y, λ a regularization parameter that controls the determined trend smoothness, and $D_2 \in R^{T \times T}$is a second-order difference operator of a Toeplitz matrix. The closed equation of trend is $\hat{Y}_{trend} = (I + \lambda D_2^T D_2)^{-1} X$ and I denote the identity matrix.

$$\tilde{Y} = Y - \hat{Y}_{trend} (3)$$

Thus, the proposed approach obtains the detrended PPG signal from the outcome of equation (3).

3.2.2 Secondary Denoising – PVC Detection and PLI noise removal

In the secondary denoising method, the proposed methodology aims to detect PVC and eliminates the PLI noise by adopting the wavelet transform method. Many additive artifacts interfere with PPG signal acquisition, including muscle artifact, arrhythmia, PLI, and low amplitude, which heavily corrupt the PPG signal. Normally, pulse wave signals exhibit multiple noise interference, affected by the instruments during the signal acquisition process. A prominent high-frequency artifact in the PPG signal is the power line interference noise. This high-frequency noise poses incompetent for further processing the PPG signals. Thus, the proposed system employs a WT-based denoising method to remove it.

WT is a filtering method that decomposes the PPG signal into multiple resolutions and generates a patch of low and high-frequency signal components represented as Approximation Coefficients (C^{App}) and Detailed Coefficients (C^{Det}), respectively. In this work, the proposed methodology applies WT for the PPG signals ($\widetilde{\boldsymbol{Y}}$)consists of 'n' number of samples represented as ($\widetilde{\boldsymbol{Y}}$) = [P(1), P(2),..., P(n)], and decomposed the input signals into different levels of resolution and obtain the signals in terms of wavelet coefficients as Approximation Coefficients (C^{App}) corresponding to low-frequency signals and Detailed Coefficients (C^{Det}) corresponding to high-frequency signals through the digital filtering process. These decomposition level are iterated up to several levels and generates the next approximation (C^{App}_1, C^{App}_2,....,C^{App}_N) and high-frequency components (C^{Det}_1, C^{Det}_2, ..., C^{Det}_N). To determine the optimum decomposition level and noisy high-frequency components among the detailed coefficients, the proposed approach employs the Crest Factor (CF) metric to measure the high amplitude signals and the Root Mean Square (RMS) signal value. Also, the proposed approach primarily aims to identify the PVC occurrence from the detailed coefficients. Hence, the CF_i is a wavelet coefficient at level 'n' is represented as,

$$\mathbf{CF_i} = \frac{\mathbf{max}\ (|\mathbf{C^{Det}}|)}{\mathbf{RMS}\ (\mathbf{C^{Det}})} \quad \mathbf{(4)}$$

From equation (4), the proposed approach obtained the appropriate decomposition, attained the signal and noisy components, and found the threshold value to identify the optimal decomposition level. It assumes the CF threshold value for obtaining the optimum decomposition level from the inspiration of the research work [22]. Hence, the proposed methodology obtained the optimum detailed coefficients (C^{Det}_O) after the estimation of CF for the noisy ($\widetilde{\boldsymbol{Y}}$) signals.

i) Premature Ventricular Contraction (PVC) Detection:

After obtaining the optimum decomposition level for detailed coefficients, the proposed methodology detects the PVC-induced PPG signals from the optimum detailed coefficient, such as high-frequency components, and retains those PPG signals for signal reconstruction.

The signal quality is vastly compromised by various cardiac-related factors involving PVC and others. In this work, the proposed approach focuses on analyzing and retaining the cardiac-related factor as PVCs because it indicates the potential heart disease and reflects the information that was more advantageous in detecting various cardiac abnormalities. Premature heartbeats originating from the ventricles, called PVCs cause irregular heartbeat, disturbing the chest's normal heart rhythm. Even though PVCs-induced PPG signals are noise signals, PVCs are pervasive in healthy subjects and patients and are correlated with several diseases involving ventricular fibrillation, Ventricular Tachycardia (VT), coronary artery disease, hypertension, and others. Hence, detecting the PVCs-induced PPG signals is imperative to emphasize further PPG signal processing. This work employs the WT method and PVC-threshold-based condition for identifying the morphological changes of the PPG signals affected by PVC. Generally, the PVC energy value is higher compared to normal PPG. Here, the PVC detection process from the basis of PVC-threshold-based condition based on the mean value of PPG signal energy on optimum decomposition coefficient levels(C^{Det}_O). It considers one threshold for each decomposition level based on the mean energy value of the PPG signal in each minute.

According to Parseval's theorem, it computes the signal energy for the high-frequency (C^{Det}_O) wavelet coefficients. For instance, assume v[n]as the sample of energy wavelet coefficients, the detailed coefficient, and the temporary variable Vp_temp, which stores the temporary energy sample value. If the detailed coefficient sample v[n] value is higher than the PVC-threshold value, the proposed methodology stores the sample value in the temporary variable Vtemp. Similarly, the proposed methodology evaluates each value Vtemp with the subsequent sample. Then, Vtemp stores the current sample and Vp_temp for the previous. If the current Vtemp is less than the previous Vp_temp, a vector $V_P[n]$ stores the Vp_temp sample, represented as $V_P[n]$ = Vp_temp, which shows the PVC occurrence. Hence, each energy coefficient sample is computed and compared with a PVC-threshold value, and if the energy coefficient sample is higher than the PVC-threshold value, the corresponding sample is considered as a PVC signal. Hence, this stored sample will be compared with the next remaining samples. Finally, this process is repeated until the highest amplitude peak representing the maximum energy value shows the PVC occurrence in the high-frequency (C^{Det}_O) wavelet coefficients. After PVC detection, the proposed methodology eliminates the PLI noises from the non-PVC induced signals.

ii) Power Line Interference Noise (PLI) Removal:

The conventional wavelet thresholding value selection method for the detailed coefficients requires estimating noise variance at each signal decomposition level, leading to poor signal denoising or distortion. Thus, this method optimizes the detailed coefficients (C^{Det}) threshold value and removes the high-frequency wavelet coefficients based on the CF-based threshold value. This proposed approach performs a hard thresholding method on the detailed coefficients of each level (C^{Det}_1, C^{Det}_2, ..., C^{Det}_N).It is represented as

$$\hat{C}^{Det}{}_{i,n} = \begin{cases} C^{Det}{}_{i,n}\ ; & \left|\left(C^{Det}{}_{i,n}\right)\right| \geq \delta \\ 0\ ; & \text{otherwise} \end{cases} \quad (5)$$

Where $C^{Det}_{i,n}$, denotes the noisy detailed coefficients and $\boldsymbol{\hat{C}^{Det}{}_{i,n}}$ represents the detailed denoised coefficients at the level of i. In the above equation, the proposed approach defines the threshold parameter, $\boldsymbol{\delta}$ based on the CF value obtained from equation (5), and it is defined as, $\boldsymbol{\delta_i = \alpha \cdot \max\left|\left(C^{Det}{}_{i,n}\right)\right|}$, where$\boldsymbol{\alpha}$ is the adjustable parameter denoted as $\frac{\boldsymbol{CF_i}}{\boldsymbol{CF_1}}$. If the detailed wavelet coefficient is less than the threshold value, it is classified as noise and replaced by zero. The signal is retained if it is greater than the threshold value. Finally, the proposed methodology uses Inverse Wavelet Transform (IWT) and reconstructs the denoised PPG signals from the signal components and approximate components. It reconstructs the PPG and PVC-induced PPG signals obtained from the decomposed high-frequency signals. Finally, the denoised signals are normalized to detect cardiovascular diseases.

4. Experiment and Performance Analysis

The performance analysis of the raw and filtered PPG signals is described in this section and determines the effectiveness of the improved denoising methods and signal quality enhancement. The performance is validated for the improved denoising methods by employing Ubuntu 16.04 operating system with Python libraries.

Dataset: To test the filtering performance of the improved denoising methods, the experimental framework employs the Beth Israel Deaconess Medical Centre (BIDMC) dataset [23]. This dataset comprised 53 recordings, each of 8-minute duration consisting of signals sampled at 125 HZ such as PPG, ECG signal, and impedance respiratory signal. Each record involves only a subset of the waveforms, signals, and time series, as numeric data. The signal was obtained from critically ill-patients recorded at Beth Israel Deaconess Medical Centre, USA. The signals in this dataset are manually annotated by the individual's breaths. The data fields in the BIDMC dataset contain Time, RESP (R), PLETH (P), V (V), AVR (A), and II (I), in which PLETH and RESP are PPG waveforms representing the uncalibrated respiration waveform, estimated from thoracic impedance and uncalibrated raw output of fingertip plethysmograph respectively. Moreover, V, AVR, and II refer to the voltage, lead values obtained from the unipolar right arm, and lead values obtained from the left leg-right arm electrodes, respectively.

4.1. Performance Analysis

The signal quality is measured before and after filtering the signals at the primary and secondary denoising steps to assess the significance of the proposed denoising method. The results illustrate the differences in the PPG signal by applying the improved denoising methods in a sequential step, which involves (i) Raw PPG signal, (ii) after the Primary Denoising-based artifacts removal, (iii) after the Secondary Denoising-based Premature Ventricular Contraction detection and Power-Line Interference noise removal. Figure 5 depicts the raw PPG signal, referring to the signals before pre-processing. In Figure 5, input data distributions of the raw PPG signals are shown over the time points. 'R' plot shows the 'RESP' signals, the 'P' plot depicts the 'PLETH signals, the 'V' plot shows the 'V signals, the 'A' plot shows the 'AVR' signals, and the 'I' plot shows the 'II' signals.

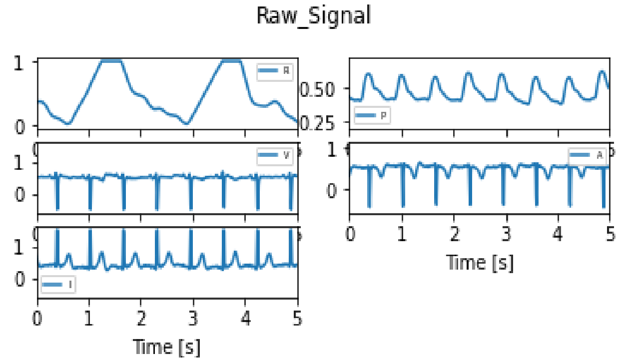


Figure 5. Raw PPG signal

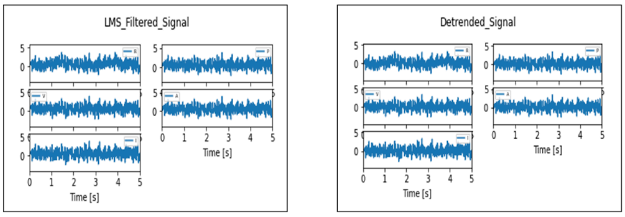
The quality of the filtered PPG signal from the raw PPG signal on the BIDMC dataset is compared using several Signal Quality Indices (SQI) [24], such as the Skewness, Kurtosis, Entropy, and Signal-to-Noise Ratio (SNR).

- **Skewness:** Measure the degree of distortion from the normal distribution of the PPG signals, resulting in the lack of symmetry in the probability distribution.
- **Kurtosis:** Measure of outliers in the distribution, representing a peakedness or flatness of the distribution from the normal distribution.
- **Entropy:** Measure uncertainty in the signal, quantifying the difference between the Probability Density Function (PDF) and normal signal distribution.
- **SNR ratio:** Measure the ratio between the signal variance and noise variance in the filtered signal with reference to the background noise.

4.1.1 Evaluation of Primary Denoising in the proposed methodology

The Performance of the Primary Denoising method is depicted in Figure 6, visualized for 5 seconds of observation of the signals with five parameters to show the fluctuations in the filtered samples. The primary denoising method involves a coarse-grained filtering process for BLW and MA noise removal and a fine-grained filtering process for refined signal further filtering.

From Figure 6(a), it is observed that there is a difference in the amplitude of the raw PPG signal, which indicates the signal components with marginal noisy waveforms and slightly improved the signal quality while applying the designed TANC-based noise cancellation method on the raw PPG signal. The filtered signal termed refined signal, which indicates the output of the coarse-grained filtering process in the primary denoising method, removed the major noises, such as BLW and MA noises, in the raw PPG signal and delivered the refined signal. Though, there is still a small amount of noise observed in the TANC method. Figure 6 (b) shows the refined signal's fine-grained filtering process. The fine-grained filtering outcomes a smooth signal after applying the detrended filter to the refined signal, resulting in the systolic and diastolic signals without dicrotic notches.

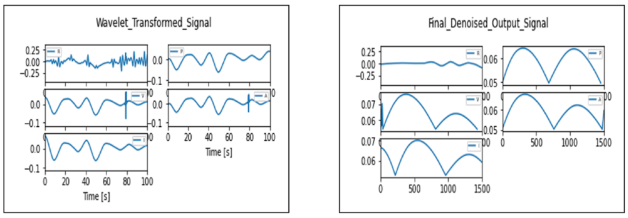


(a) Coarse-grained Filtering (b) Fine-grained Filtering

Figure 6. Plot of Filtered Signals in Primary Denoising

4.1.2 Evaluation of Secondary Denoising in the proposed methodology

The proposed system performs the secondary denoising using the WT method to remove the noisy components from the signals filtered from the primary denoising method. The impact of crest factor and energy level measure on the PPG signal's optimum decomposition level is illustrated in Figure 7(a), depicting the filtered PPG signals with the optimal decomposition level for the PVC detection, visualized for 100 seconds. Figure 7(b) shows the clear systolic and diastolic waveforms after removing the PLI noises from the non-PVC signals through the crest factor-based high-frequency signal analysis, visualized for the number of samples.



(a) Optimal Level for PVC Detection (b) PLI Noise Removal

Figure 7. Plot of Filtered Signals in Secondary Denoising

Transformation of each signal variable from the raw input to the final filtered output is visualized in Figure 7 for the variables considered for pre-processing. Thus, it is concluded that the proposed approach improves the signal quality after filtering the raw PPG signals using an improved denoising method and facilitates cardiovascular detection performance.

Table 1: SQI Measures between Raw and WT Filtered Signal

Signal Parameters	SQI Measures			
	Kurtosis	Skewness	Entropy	SNR
RESP (R)	0.5274	0.1281	10.9783	-0.0073
PLETH (P)	-0.0021	-0.4975	10.9526	-0.01095
V (V)	0.4041	-0.5547	10.9594	-0.00088
AVR (A)	0.3124	0.5719	10.9605	-0.00716
II (I)	0.0601	-0.5059	10.9515	-0.00082

Table 1 describes the signal's quality measures before and after pre-processing performed by the WT method. The SQI metrics are employed with the difference measured from the raw signal to examine the significance of the filtered or denoised PPG signal. The primary and secondary denoising method greatly assists the representation of the input signal without removing the potential signal components, which are quantified through the metrics of entropy and SNR. Moreover, the skewness and kurtosis measures indicate the distortion and outliers present in the filtered signal compared with the raw input signal. From the analysis of Table1, it is recognized that the proposed pre-processing scheme retains the vital signal components that show the representation of the input signal without certain noisy values rather than ignoring all the uncertain and outlier signals. Thus, the signal components without the noisy components in the PPG signals facilitate the accurate recognition of cardiovascular diseases.

5. Conclusion

This paper designed an effective pre-processing technique that improves denoising methods to enhance the quality of PPG signals and consequently improve the detection of cardiovascular diseases. The proposed pre-processing technique involved two major phases: primary denoising based on BLW and MA artifacts removal and secondary denoising based-PVC Detection and PLI noise removal from the PPG signals. In primary denoising, the proposed approach performed the coarse-grained and fine-grained filtering using two-stage adaptive canceller and detrended filtering, respectively. In secondary denoising, it detected and retained the PVC-induced PPG signals and removed the high-frequency PLI noise from the non-induced PPG signals to obtain noise-free PPG signals. Finally, the proposed methodology reconstructed the denoised signals obtained from the WT Transform method and the PVC-induced PPG signals by adopting the IWT transform method and obtained the denoised PPG signals. Thus, the SQI measures are quantified for the filtered signals with reference to the raw input signal.

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