Investigating the Application of Wavelet Basis for HRV Determining

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***Abstract*— The paper presents methods for extracting heart rate variability time series. An algorithm based on wavelet analysis and first derivative calculation is proposed and implemented programmatically. Preprocessing of the input data was performed in order to reduce external interference, remove zero-line drift and artifacts of different origins. Various wavelet bases have been investigated and applied in the cardiac time series determination procedure. Daubechies wavelet bases with different number of coefficients and at different levels of decomposition of the studied data were studied. The proposed algorithm was tested on cardio series obtained by photoplethysmographic method. Standard time domain parameters are also defined. The presented numerical and graphical results were obtained using the software program created in the Visual Studio environment.**

Keywords*— *Cardiovascular Diseases, Heart Rate Variability, PPG, Preprocessing.

I. Introduction

Photoplethysmography (PPG) is a non-invasive optical technique for measuring changes in blood volume in tissues, mainly used for monitoring the cardiovascular system. Photoplethysmographic signals are obtained by measuring the absorption of light by the skin, with blood flow affecting the amount of light reflected or absorbed.

The sensor recording the photoplethysmographic signal is usually a non-invasive optical sensor used to monitor blood volume changes in tissues. Key physiological data such as heart rate, blood oxygen levels can be extracted from the PPG signal, and reliable information about cardiovascular health can be obtained. The photoplethysmography method works by shining light (usually an infrared or green LED) onto the skin and measuring the amount of light that is absorbed or reflected by the blood vessels. Changes in blood volume correspond to changes in light absorption, and through these fluctuations the PPG signal is captured.

The main components of any PPG device include:

- A light source (LED) emitting light that penetrates the skin of the human body and interacts with the blood vessels beneath the surface.
- A photodetector that measures the intensity of reflected or transmitted light. The amount of reflected light varies with blood flow.
- A signal processor that serves to analyze the raw signals and extract useful physiological parameters such as heart rate or SpO2 (oxygen saturation).

Different types of PPG devices have been created and are successfully used today to receive PPG signals:

Wearable devices that are typically integrated into smartwatches, fitness trackers, and health trackers. Devices such as the Apple Watch, Fitbit and Garmin use PPG technology to measure heart rate and track fitness activities.

Medical devices that are used in hospitals, clinical settings, and have already entered the everyday life of people such as pulse oximeters, usually attached to the tip of a finger and used to measure oxygen levels in the blood.

There is a growing application of mobile health sensors that are used in mobile health applications and connected health systems for continuous health monitoring.

Photoplethysmography is used in healthcare to monitor heart rate. By detecting the time between pulses, PPG devices can provide real-time heart rate data.

Another application of photoplethysmography in healthcare is the measurement of blood oxygen saturation. In pulse oximetry, PPG devices can assess the level of oxygen in the blood, which is critical for patients with respiratory problems or sleep apnea.

A major application of PPG signals is heart rate variability (HRV) analysis. HRV is an important measure of autonomic nervous system function, and PPG devices can analyze beat-to-beat variability. Heart rate variability is now increasingly being used to track stress and sleep [1]. Many wearables use PPG to monitor stress levels and analyze sleep patterns based on heart rate and breathing rate variability.

A methodology has been created using photoplethysmographic and electrocardiographic signals to assess arterial pressure. Some advanced PPG devices, in combination with algorithms and secondary sensors, are used to assess blood pressure [2,3].

Advantages of PPG devices

- Non-invasiveness: PPG technology does not require invasive procedures such as blood sampling or surgery.

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- Convenience: It is easy to use and can be built into compact wearables, making it suitable for long-term health monitoring.
- Affordability: PPG devices are relatively inexpensive compared to other medical diagnostic tools such as electrocardiograms (ECGs).

Characteristics of PPG signals that may affect their widespread use:

Accuracy Variability - Accuracy can be affected by motion, skin color, and interference from ambient light, especially with wearable devices during physical activities.

Limited Clinical Effectiveness - Although PPG is excellent for monitoring heart rate and blood oxygen, it cannot provide as detailed cardiovascular information as an ECG.

The purpose of this paper is to present methods for extracting heart rate variability time series through the use of discrete wavelet transform. Daubechies wavelet bases with different number of coefficients and at different levels of decomposition of the studied data were studied.

II. DISCRETE WAVELET TRANSFORM

The Discrete Wavelet Transform (DWT) is a mathematical technique used to break down a signal or data set into different frequency components at various scales. Unlike the Fourier Transform, which analyzes signals purely in the frequency domain, DWT allows for both time and frequency localization. This makes it particularly useful for analyzing non-stationary signals - signals where frequency components change over time.

A. Main characteristics of DWT

- Multiresolution Analysis: DWT represents data at different resolutions by decomposing the signal into low-frequency and high-frequency components at multiple levels (Figure 1). This allows for a more detailed analysis of the signal.
  In the Discrete Wavelet Transform, low-pass and high-pass filters play a key role in the process of decomposing the signal into different levels of detail.
  - Low-pass filter (Approximation Coefficients)
  This filter captures the smooth components of the signal associated with low frequencies. After filtering, the main trends in the signal are preserved, such as larger changes, or "global" features.
  The result of applying the low-pass filter is called approximation coefficients, which contain the rough representation of the signal at a given level of transformation.
  - High-pass filter (Detail Coefficients)
  This filter captures the finer details of the signal associated with high frequency components. It extracts the subtle oscillations and changes in the signal that are visible at higher frequencies.
  The result of applying the high-pass filter is called detail coefficients, which contain information about "local" details and rapid changes in the signal.
  At each DWT iteration, the signal is split into two parts:
  - Low frequency (smooth component) through the low-pass filter.
  - High frequency (detail) through the high-pass filter.
  This process is repeated at each level, with the approximation from the current level subjected to a new decomposition with new filters. Thus, the signal is divided into smaller and smaller frequency bands, which allows accurate analysis of different frequencies and time components.

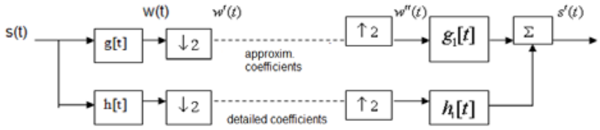

Figure 1. DWT

- Time-Frequency Localization: Since DWT is applied at various scales, it allows for the identification of both when and at what frequency certain patterns or events occur.
- Efficient Computation: DWT is computationally efficient compared to the continuous wavelet transform, as it only computes values at discrete intervals.

B. Fields of application of the Discrete wavelet transform

DWT is widely used in various research fields due to its ability to analyze signals in both the time and frequency domains, making it a suitable technology for use in a number of applications:

- Signal and Image Compression

DWT is used in image compression standards such as JPEG 2000. It effectively compresses images by dividing them into multiple resolution representations, allowing high degrees of compression without significant loss of image quality. DWT is also used in audio compression because it offers better time-frequency localization than the Fourier transform.

- Biomedical signal processing

DWT helps PPG/ECG signals processing and analysis, detect heart rate variability, and extract features for cardio data classification.

DWT is used to analyze brain wave patterns (EEG - electroencephalogram) to diagnose neurological conditions such as epilepsy by detecting spikes and seizures.

- Data denoising

Noise reduction: In various fields, such as telecommunications and audio engineering, DWT [4] is used to filter noise from signals without distorting the underlying information. This is commonly applied in medical, seismic and financial time series data.

- Image recognition and feature extraction

DWT is used in machine learning and pattern recognition to extract features from datasets, especially for image and speech recognition. For example, it helps extract textural features in images or important features in audio signals.

- Digital Watermark

In the field of digital watermarking, DWT is used to embed information (such as copyright data) in digital media such as images and audio. The transformation makes the watermark resistant to various manipulations, such as compression and resizing.

- Seismic data analysis

DWT is used in geophysics to analyze seismic signals, helping to identify and locate waveforms that indicate earthquakes or oil reservoirs.

- Economics and financial analysis

In financial time series analysis, DWT is used to analyze stock prices, interest rates, and other economic indicators by separating them into different frequency components, allowing for trend detection and noise filtering.

- Object recognition

DWT is used for object recognition and image classification by decomposing images into different frequency bands, which can improve the accuracy of algorithms by focusing on key image features.

- Speech processing

DWT is used to improve speech recognition systems by helping to separate noise from useful speech patterns and improving recognition accuracy in noisy environments.

- Astronomy

Astronomers use DWT to detect and analyze cosmic signals and waves, such as in the detection of gravitational waves and the analysis of astrophysical phenomena from noisy data.

III. DENOISING

Preprocessing is one of the important steps [5,6] in the PPG peak detection task. This step aims to remove components that do not belong to the signal but are the result of various noises.

A normal PPG pulse wave frequency ranges from 0.5 Hz to 5 Hz, but when PPG signals are contaminated, the high frequency range can reach up to 20 Hz. The PPG signal is often accompanied by high-frequency noise elements, which are removed with a low-pass filter with a cutoff frequency of 5Hz. Noise covers a different range of frequencies. Baseline drift noise caused by respiratory activity has a frequency range of 0.15–0.3 Hz; the normal respiratory frequency range is about 0.04–1.6 Hz, and the motion artifact range is 0.1 Hz [7,8].

A graph of a PPG signal with its main characteristics is shown in Figure 2. The figure shows the two consecutive peaks observed in the photoplethysmographic signals:

Systolic peak - the main and highest peak [9] in the PPG signal. It reflects the systolic ejection of blood from the heart to the peripheral vessels, resulting in an increase in arterial blood volume and increased light absorption. This peak is related to the cardiac cycle and occurs with each heartbeat.

Diastolic Peak – A smaller secondary peak that occurs after the main systolic peak. This is a reflected wave that travels back through the arteries from the peripheral vessels to the heart. The diastolic peak is due to arterial elasticity and in some cases can be used to assess arterial stiffness.

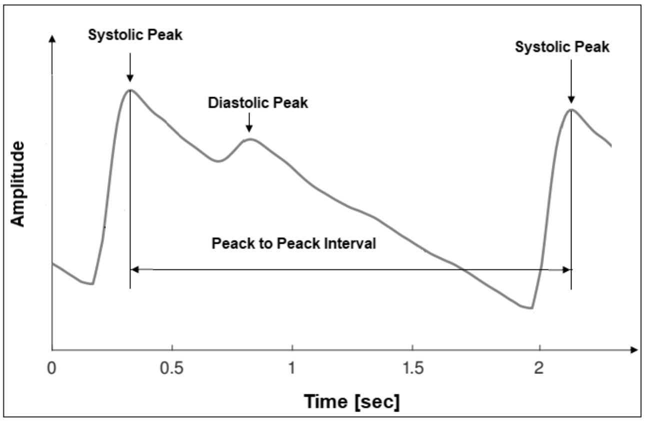

Figure 2. PPG signal

Noise reduction in photoplethysmography signals is important [10] because these signals are often contaminated by various types of noise, such as patient motion, electromagnetic interference, and baseline drift. Effective noise removal improves the accuracy of calculations for heart rate, blood oxygenation and other physiological parameters.

Basic methods for reducing noise in PPG signals:

1. Noise reduction with the use of filters (classical, digital, adaptive). Classic filters are for example:

Low-pass filters - remove high-frequency noise that may be the result of external sources of electromagnetic interference or sensor noise.

High-pass filters - remove low-frequency noise, such as baseline wander, which may be due to breathing activity or skin movements.

2. WT based methods

Discrete wavelet transform (DWT) is one of the most effective wavelet methods [11-14] for reducing noise in PPG signals. By splitting the signal into different frequency components, DWT allows the removal of specific noise components while preserving the essential information in the signal. See more about this in my above answer.

3. Adaptive Noise Cancellation (Adaptive Noise Cancellation):

This method uses a second sensor to record the noise and removes it from the original PPG signal using adaptive algorithms such as Least Mean Squares (LMS).

4. Methods based on machine learning algorithms:

Neural networks [15-17] or Support Vector Machines (SVMs) can be trained to recognize and remove noise in real time, based on large datasets of PPG signals.

A diagram of the main techniques for reducing noise in signals is presented in Figure 3.

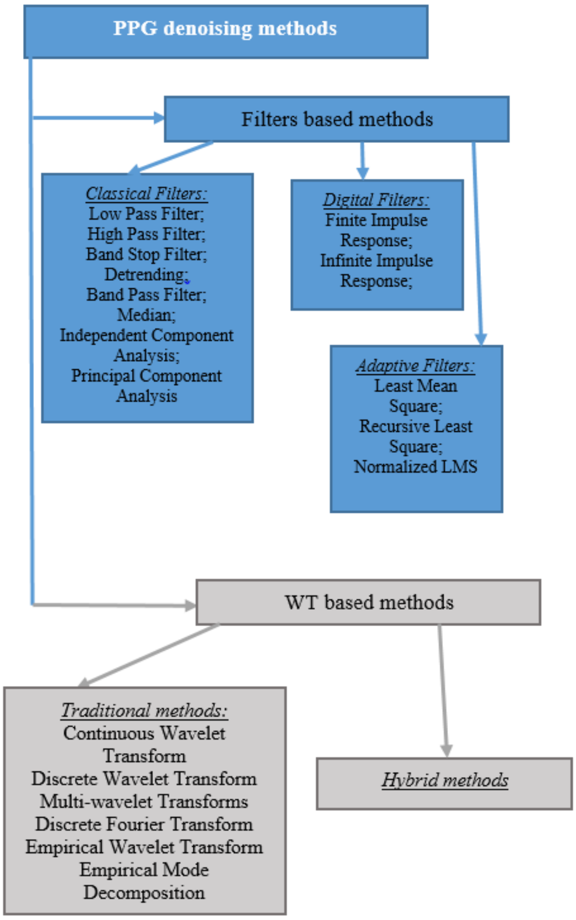

Figure 3. Denoising PPG methods

1. Noise reduction

Photoplethysmographic signals contain various types of noise [18-20], such as artifacts derived from human movement, electromagnetic interference, or ambient noise. Filtering is usually done at this stage, and various noise reduction filters can be used:

- Bandpass filter: Helps remove high-frequency noise as well as low-frequency components.
- Low-pass filter: Removes high-frequency noise caused, for example, by electromagnetic interference.
- High-pass filter: Removes low-frequency fluctuations such as those caused by human breathing or body movement (or some parts of it, for example moving the hands).
- Notch filter: Can be used to remove specific frequencies, for example the power supply frequency.

2. Baseline correction

Due to movement or other factors, the photoplethysmographic signal can be distorted and have variations in the baseline level (the so-called "drift"). For this, a baseline correction is applied, which stabilizes the signal and returns it to its normal state, which will allow correct analyzes.

3. Remove motion artifacts

Motion artifacts represent one of the biggest challenges in measuring photoplethysmographic signals, especially when using mobile devices to record them. Artifact removal approaches include:

• Filtering of frequencies related to motion (most often low-frequency oscillations).

• Adaptive filters, which are used to dynamically correct the signal based on output data from accelerometers (when available).

4. Signal normalization.

IV. Denoising and Peak Detection

A block diagram of the procedure for noise reduction in photoplethysmographic signals, in order to evaluate the effectiveness of the applied method, is shown in Figure 4.

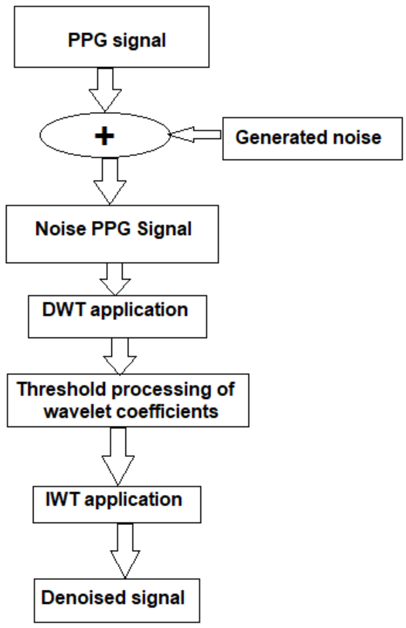

Figure 4. PPG Denoising

The noise reduction evaluation of PPG signals is done with the following parameters:

SNR – Signal to Noise Ratio;

MSE – Mean Square Error;

PDR – Percentage Root Mean Square Difference.

Detection of maximum signal deviations

The procedure includes: 1. Discrete Wavelet Transform on data, obtaining detailed and approximate coefficients. Investigated the influence of the following wavelet bases: Daubechies with different coefficients. 2. Threshold processing of detailed coefficients and compilation of the set of candidates for peaks. 3. Analysis of sets of candidate peaks, and final determination of S peaks. 4. Inverse WT.

The parameters were used to study the detection accuracy [21]:

$$Sensitivity\ (Se) = TP/(TP + FN) \quad (1)$$

$$Positivity\ Predictive\ (PP) = TP/(TP + FP) \quad (2)$$

$$DER\ (Detection\ Error\ Rate) = (FP + FN)/TB \quad (3)$$

V. RESULTS

The presented numerical and graphical results were obtained using the software program created in the Visual Studio environment.

A. Denoising

Table I shows results of PPG denoising using different basis. Researches have been carried out with Dobyshy wavelet bases with different number of coefficients (2, 4, 6, 8, 10, 12 and 20). The obtained results point to an optimal Daubechies basis with 4 coefficients.

TABLE I. TIME DOMAIN

WT	**SNR**	**MSE**	**PRD [%]**
Haar	4.22	0.98	86.60
Db4	16.33	0.08	28.84
Db6	9.38	0.52	45.13
Db8	14.51	0.12	32.44
Db10	10.72	0.43	41.25
Db12	15.02	0.11	30.24
Db20	8.24	0.16	49.03

B. Peak detection

The obtained Peak detection results with different wavelet basis are shown in Table II.

Peak detection studies were performed on six PPG signals and the estimated parameters Se, PP and DER were calculated for each individual recording. The obtained values of the evaluation parameters show that the DWT can be successfully applied for the detection of the maximum deviations in the photoplethysmographic signals.

TABLE II. PEAK DETECTION

No	**Total beats**	**Se (%)**	**PP (%)**	**DER (%)**
1	1849	97.14	93.04	1.62
2	1723	97.26	96.84	1.43
3	2011	98.23	94.07	1.58
4	1945	96.05	93.22	1.61
5	1602	95.44	94.36	1.59
6	1883	95.01	96.91	1.48

VI. CONCLUSION

This paper presents the processing of photoplethysmographic signals, which includes preprocessing and detection of maximum deviations in the signals. The most important process in preprocessing is to remove noise from the signal, which results in improving the quality of the PPG signal and enabling the efficiency of subsequent processes. Noise Reduction and HRV Determining are Essential for Heart Rate Variability Assessment and Cardiovascular Disease Analysis.

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