Multiresolution analysis of poor remote photoplethysmography signal using wavelet transform*

Ihor Berezhnyi[1,*,†], Adrian Nakonechnyi[1,†]

[1] Lviv Polytechnic National University, 12, Bandera Str, Lviv, 79013, Ukraine

Abstract

Remote photoplethysmogram signal processing algorithms have demonstrated effectiveness as a non-invasive means of gathering data on the human cardiovascular system for rapid clinical parameter assessment. The primary objective is to extract valuable information from remote photoplethysmogram signals captured by common front cameras on smartphones or laptop webcams for subsequent analysis of the human cardiovascular system. The developed approach to processing a remote photoplethysmogram obtained from a low–quality video signal using a discrete wavelet transform and deconstruction–reconstruction allows filtering and qualitatively evaluating the received signal to predict possible diseases of the human cardiovascular system. The selection of optimal mother wavelet functions provides high performance and scalability of the system in the time–frequency domain. According to the developed approaches of multiresolution analysis, the reliability of the obtained data is more than 93% and makes it possible to conduct time–resolved analysis of a low–quality video signal and identify key points of the human cardiovascular system.

Keywords

Photoplethysmography, heart rate, variability, filtering, wavelet transform

1. Introduction

1.1. Remote photoplethysmography

Remote photoplethysmography (RPPG) has transformed the field of physiological monitoring by providing a non–invasive way to assess vital signs using camera–equipped devices from a distance. As telemedicine and remote healthcare continue to grow, RPPG signal analysis is essential to provide accurate and reliable health assessments across traditional clinical settings.

RPPG is a non–invasive optical method that is widely used in a variety of medical and physiological studies. Its importance stems from several key factors that make it significant in clinical and research settings, such as non–invasiveness, versatility, accessibility, and cost–effectiveness [1]. Non–invasiveness and convenience RPPG is performed using a non–invasive sensor. This makes it a comfortable method for patients, allowing for regular or continuous monitoring. RPPG provides vital information about the human cardiovascular (CV) system. It measures changes in blood volume in the microvascular flow of tissues, which are indicative of the pulsatile information component of the cardiac cycle. RPPG waveforms are used to calculate arterial blood oxygen saturation and determine heart rate in pulse oximeters, which are widely used in routine clinical practice [2].

This capability makes RPPG useful for monitoring heart rate, blood oxygen saturation (SpO2), and other hemodynamic parameters. In clinical settings, RPPG is used for anesthesia monitoring, sleep studies, and autonomic function assessment. RPPG devices are relatively inexpensive and simple compared to other cardiovascular monitoring technologies such as electrocardiography

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* Corresponding author.
† These authors contributed equally.
ihor.v.berezhnyi@lpnu.ua (I. Berezhnyi); adrnakon@gmail.com (A. Nakonechnyi)
0009-0003-4938-7947 (I. Berezhnyi); 0000-0002-1873-6337 (A. Nakonechnyi)

(ECG) or echocardiography (EEG) [3, 4]. This affordability makes RPPG accessible in both high and low resource settings.

1.2. Problem statement

Today, there are a variety of methods for extracting the RPPG signal from the camera video stream, as well as filtering algorithms [3], but most of them are designed for systems with a large number of frames, most often 60fps (frames per second), and high FHD resolution. Such algorithms are inefficient and unworkable with the front–facing cameras of common smartphones, laptops, and notebooks, which have frame rates of 15fps to 30fps at low SD and HD resolutions. One of the key problems is the loss of information in the RGB signal and image distortion due to low resolution and high noise levels (lighting changes, motion in the frame, etc.) in the video stream [1, 5]. This leads to difficulties in analyzing the necessary critical points of the human cardiovascular system (CVS) for the analysis of RPPG signals, such as:

- Reduced accuracy of face and key point extraction: Poor video quality makes it difficult to accurately extract the face area and identify key points [4]. This adversely affects the subsequent analysis of the RGB signal and facial skin color fluctuations required for RPPG signal extraction.
- Noise and artifacts present in low–quality video can mask real skin color changes caused by blood pulsation [4].
- Low image resolution leads to reduced spatial clarity and unwanted artifacts, which makes it difficult to analyze changes in RGB space [5].
- Variable lighting makes it difficult to normalize colors and further complicates the extraction of skin–color–dependent signals. In conditions of low video quality, this effect becomes even more pronounced and significantly distorts the received RPPG signal [6].

1.3. The purpose of the study

The aim and objective of the study is to develop an algorithm and principles for processing RPPG signals received from laptop webcams or smartphone front cameras with low fps (15–20fps) by using wavelet transform and wavelet filtering of the received signals, as well as the deconstruction–reconstruction method. Analysis of received wavelet coefficients and separation of specific coefficients that contain information about the human nervous system. This involves the development of an algorithm for multi–resolution filtering of the input signal (RPPG) and identification of key points necessary for the analysis of the human cardiovascular system. Selection of mother wavelet functions for filtering RPPG signals by comparing the obtained results with medical devices. Analysis of the received wavelet coefficients in the time-frequency domain. Forming a scalogram to compare the RPPG signal before and after filtering.

2. Materials and Methods

2.1. Ethics and Dataset

The study was conducted on the UBFC–rPPG [5], PURE [6], SCAMPS [7], UBFC–Phys [8] datasets, as well as internal recordings using a Google Pixel 4 mobile phone. The studied datasets contain more than 120 videos with 62 subjects. These videos contain different characteristics of cameras, lighting, room, resolution, and number of frames per second. In total, videos with Standard Definition (SD), High Definition (HD), and Full High Definition (Full HD) resolutions were analyzed. The videos have a different number of frames per second, namely: 10fps, 15fps, 20fps, 30fps, and 60fps.

2.2. Wavelet transform method

Wavelet filtering is known to be a powerful signal processing tool that is widely used to analyze remote photoplethysmography (RPPG) signals. Such filtering has clear advantages and disadvantages when applied in this field. One of the most important advantages is the ability to effectively suppress noise and artifacts while preserving signal features on different time scales. The decomposition of RPPG signals into wavelet coefficients with different resolutions allows for selective noise removal, improving the signal–to–noise ratio and the accuracy of parameter estimation and signal interpretation.

Wavelet filtering is a versatile yet adaptive method for removing signal noise in RPPG analysis, allowing researchers to customize the filtering process to suit unique signal characteristics and noise sources. Wavelet filters can be tuned to specific frequency bands or spatial regions in the signal, resulting in precise noise suppression while minimizing distortion of the underlying physiological information. Wavelet filtering is a powerful tool for detecting and removing transient or non–stationary noise components in RPPG recordings that are affected by motion artifacts or environmental perturbations.

It is important to note that, like any method, it has its limitations. The complexity associated with choosing the basis functions and designing filters, especially when the signal has multiple overlapping components or nonlinearities. To achieve the best noise reduction performance and avoid artifacts or signal distortion, it is important to choose the appropriate type of basis wavelet, number of decomposition levels, and thresholding method. Wavelet filtering can introduce edge effects or artifacts at the signal boundaries, potentially affecting the accuracy and reliability of the results.

Wavelet filtering can be problematic in real–time or near–real–time applications, especially when working with large datasets or high–resolution signals. However, with proper optimization, wavelet decomposition and reconstruction can be made scalable and applicable in resource–constrained environments or in embedded systems [8]. While wavelet filtering offers significant advantages in noise suppression and signal reduction in RPPG analysis, it can be difficult for non–specialists to interpret due to the complexity of performing wavelet transforms and using appropriate thresholding methods. However, it should be noted that these limitations can be overcome with proper optimization. In general, wavelet filtering is an important and powerful tool for analyzing RPPGs, provided that the appropriate transformation characteristics are skillfully and correctly selected.

2.3. Wavelet deconstruction

The discrete wavelet transform (DWT) of RPPG signals provides time–referenced frequency information that allows us to operate on the signal and analyze its critical changes and positions in time–frequency space using the RPPG signal decomposition levels (Figure 1).

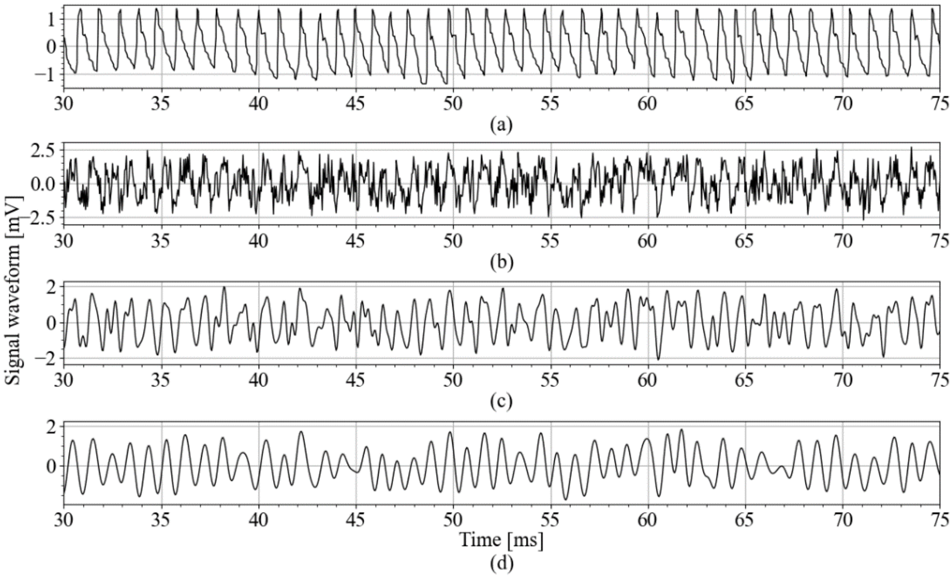

Figure 1: RPPG signals with various levels of CWT reconstruction: (a) Ground Truth signal of PPG from Pulse Oximeter (medical device), (b) origin RPPG signal using POS from video stream, (c) RPPG signal after wavelet transform filter, (d) RPPG signal with wavelet transform filter and Bandpass filter.

Figure 1 shows the plethysmogram (PPG) signal, specifically, an example of a PPG signal from a medical device obtained by RPPG from video images. The RPPG signal is presented after level 3 wavelet deconstruction–reconstruction and the RPPG signal after wavelet thresholding and decomposition coefficient filtering using a Bandpass filter with a setting of 0.7Hz. During wavelet transform or wavelet deconstruction, the resulting coefficients (Figure 2) can be interpreted as a separate component of the input signal. Such components describe the informative part of the RPPG input signal at selected frequencies, which allows the signal to be evaluated in time–frequency space. It is worth noting that the number of coefficients decreases with increasing reconstruction level, so changes from filtering bring significant changes to the original signal.

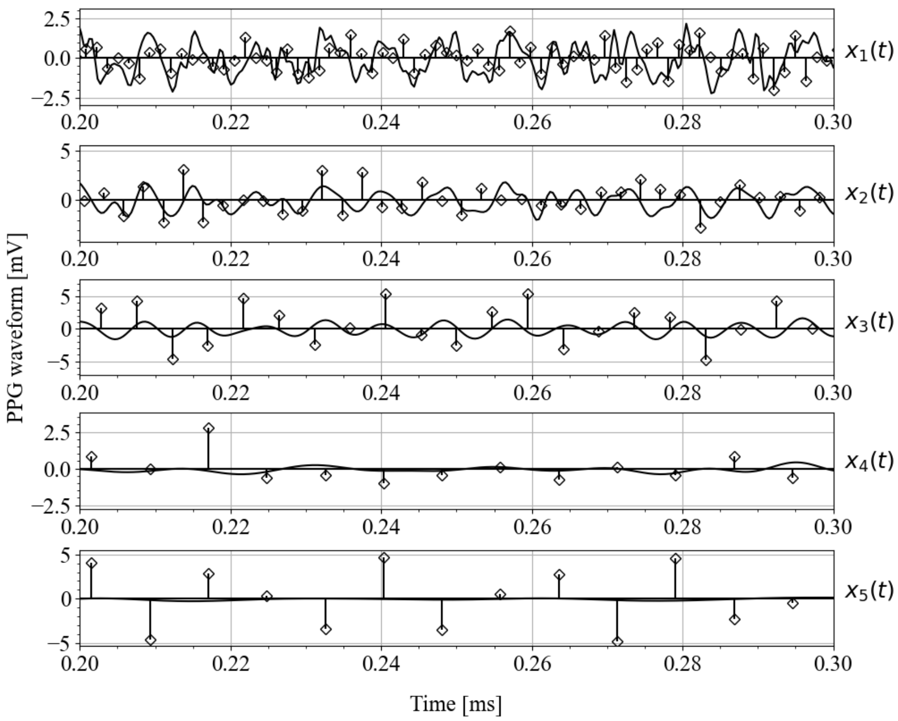

Figure 2: Discrete wavelet transform packets for five reconstruction levels with coefficients

After reconstructing the PPG signal received from the Google Pixel smartphone and the front camera resolution of 640×480px (0.3 MP) with a frame rate of 20 frames per second, the resulting RPPG signal can be represented as a set of wavelet coefficients (Figure 2). After analyzing the video from the UBFC–rPPG [5], PURE [6], SCAMPS [7], UBFC–Phys [8] datasets, it was concluded that, depending on the resolution and the number of frames per second, it is necessary to perform wavelet decomposition up to seven levels. The decomposition of the eighth and higher levels does not contain an information component for analyzing RPPG signals obtained from a low–quality camera.

The obtained decomposition coefficients can be represented as signal graphs (Figure 3), where each level corresponds to the level of decomposition of the RPPG signal. Accordingly, the zero level is the representation of the input RPPG signal, the first level of the decomposition is the composition of the signal without one coefficient in the wavelet decomposition of the signal.

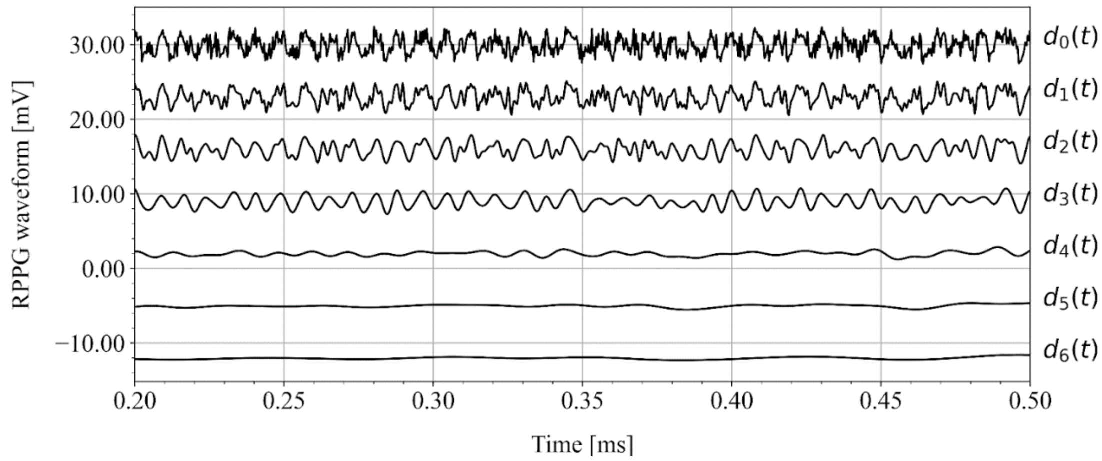

Figure 3: Discrete wavelet transform packets for seven reconstruction levels

2.4. Wavelet deconstruction

To determine the parameters of the PPG signal, namely, the systolic and diastolic peak, and variability, the obtained RPPG signal was analyzed with a level 3 wavelet decomposition. The classification of these parameters is conducted by finding the maxima and minima of the signal, taking into account their amplitude (Figure 4). A part of this signal is shown in Figure 5.

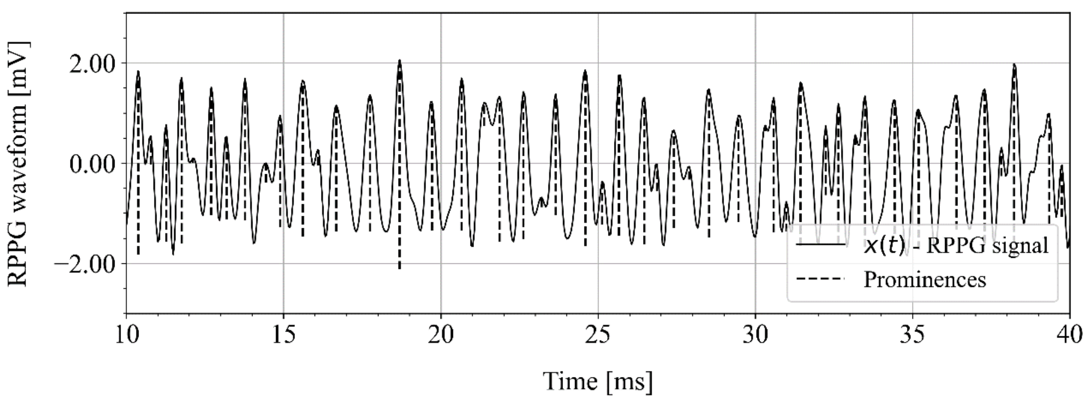

Figure 4: Result from RPPG signal after DWT reconstruction with level 3, with basic cardiac parameters

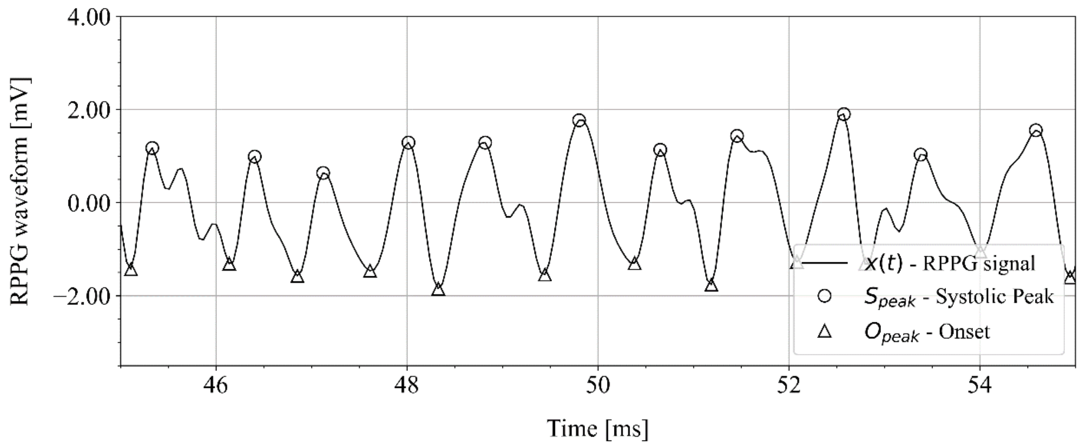

Figure 5: Result from RPPG signal after DWT reconstruction with level 3, with basic cardiac parameters

2.5. Information component of the cardiovascular system

The influence of wavelet decomposition levels on the content of the information component on cardiovascular activity is investigated. The direct dependence of some levels of the decomposition on the parameters of the cardiovascular system was found. Figure 6 shows the signal of the 3rd level of reconstruction, which corresponds to the heart rate, as well as the variability of the cardiovascular system (IBI). Figure 6 shows a comparison of the IBI signal obtained from the RPPG and the signal from the medical device. The RPPG signal contains interference such as missing frames, motion in the frame, and changes in lighting, which is tracked in the peaks that are present in the RR signal.

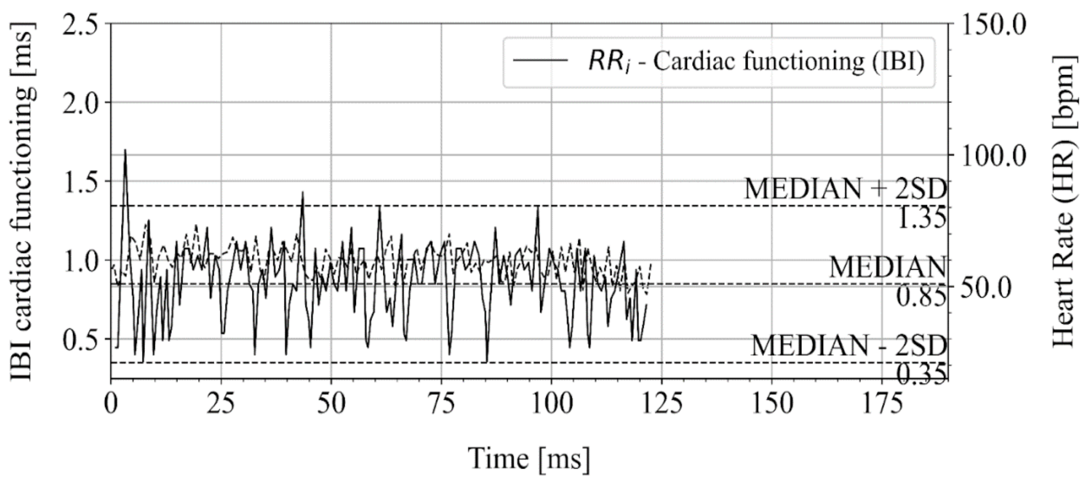

Figure 6: Result IBI signal after DWT reconstruction with level 3 of RPPG signal

This study was carried out on the specified datasets, the results of which are shown in Table 1. However, if the interference data is filtered out using a simple Bandpass filter with a level of 0.7Hz, the resulting signal will correspond to the medical signal by 85–94% (corresponding to the number of frames per second). The median of this signal will be 0.85ms, and considering the double standard deviation, to determine the permissible deviation, it will be from 0.35ms to 1.35ms. Figure 6 also shows the relationship between heart rate and the variability of the human cardiovascular system, with an average heart rate of about 55–63 beats per minute.

Table 1
Results of the wavelet reconstruction method for set of datasets

Dataset name	MEAN [ms]	MEDIAN [ms]	RMSSD [ms]	SD [ms]	Error [%]	Confidence [%]
UBFC–rPPG [1]	1.169	1.176	0.276	0.321	0.321	85.08
PURE [2]	1.097	1.118	0.298	0.33	0.397	87.27
SCAMPS [3]	1.112	1.147	1.053	0.358	0.747	78.92
UBFC–Phys [4]	1.09	1.176	0.309	0.319	0.411	89.56
Custom (15fps)	1.135	1.118	0.28	0.328	0.313	94.54

A brief explanation of the calculated parameters:

- MEAN is the root-mean-square value of the signal.
- MEDIAN is the average value of all data ordered from smallest to largest.
- RMSSD is the root-mean-square of successive differences in signal values.
- SD – standard deviation, or a statistical measure of variability that indicates the average amount of deviation of a set of numbers from their mean value.
- Error – the percentage of values with an error relative to the medical equipment.
- Confidence – the value of the correspondence between the signal from the medical device and the signal obtained as a result of wavelet transformation.

3. Architecture diagram

RPPG algorithms typically use face recognition techniques to identify regions of interest (ROIs) in the resulting images [9]. The architecture in Figure 7 describes further processing, which involves selective filtering of skin pixels based on empirically derived color thresholds, which helps to extract signals that indicate the dynamics of blood perfusion.

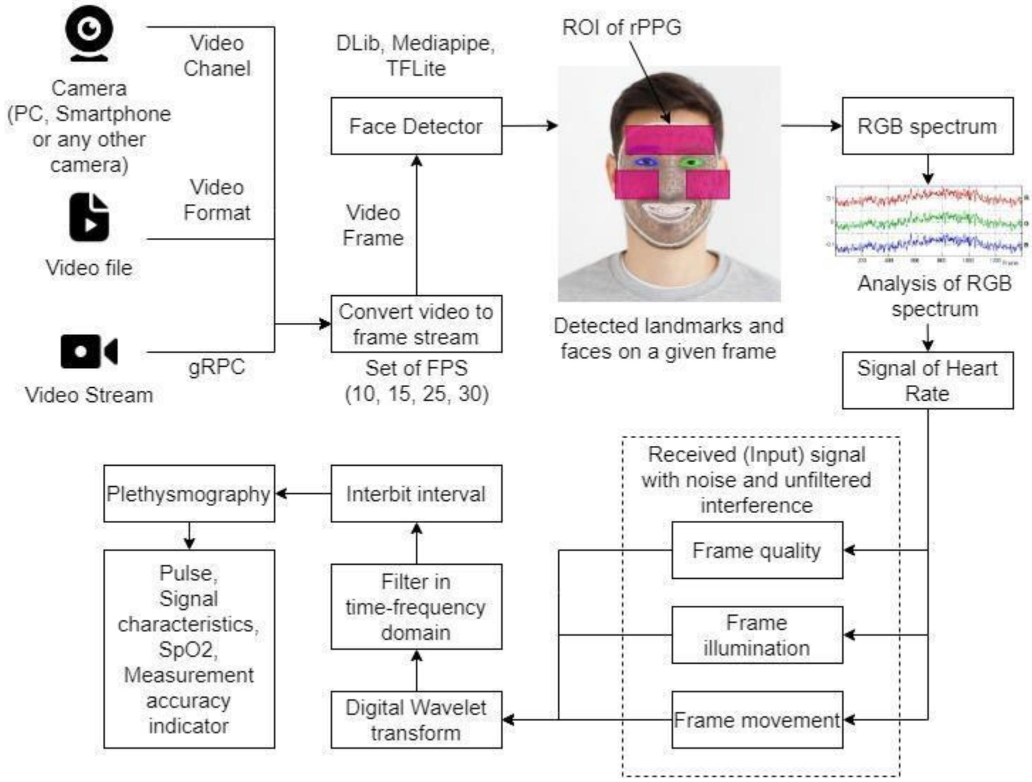

Figure 7: Architecture for determining the emergency from an input video stream in real time

Modern signal processing methods, such as clustering and Bandpass Filtering algorithms, effectively reduce the impact of negative factors such as motion artifacts and environmental noise. These algorithmic approaches facilitate non–invasive and continuous monitoring of cardiovascular parameters, which has promising implications for various fields, including healthcare, health monitoring, and human–computer interaction research [10].

The proposed architecture solves a number of problems of the remote photoplethysmography approach using the following elements:

- Video conversion and frame–by–frame reading element (this element allows processing both recorded video and video stream, regardless of whether it is a physical camera or a stream from the cloud).
- Face and landmark detection (the element of detecting faces in the frame, recognizing faces and landmark control points).
- RGB signal analysis.
- Input signal evaluation (provides control over the incoming video).
- Wavelet transform and filtering (provides time–frequency analysis of the signal with subsequent filtering).

The basic principle of multi–resolution analysis of the RPPG signal is shown in Figure 8. Different sets of mother wavelet functions were used for the study, and as a result, the dmay mother function was chosen [10, 11].

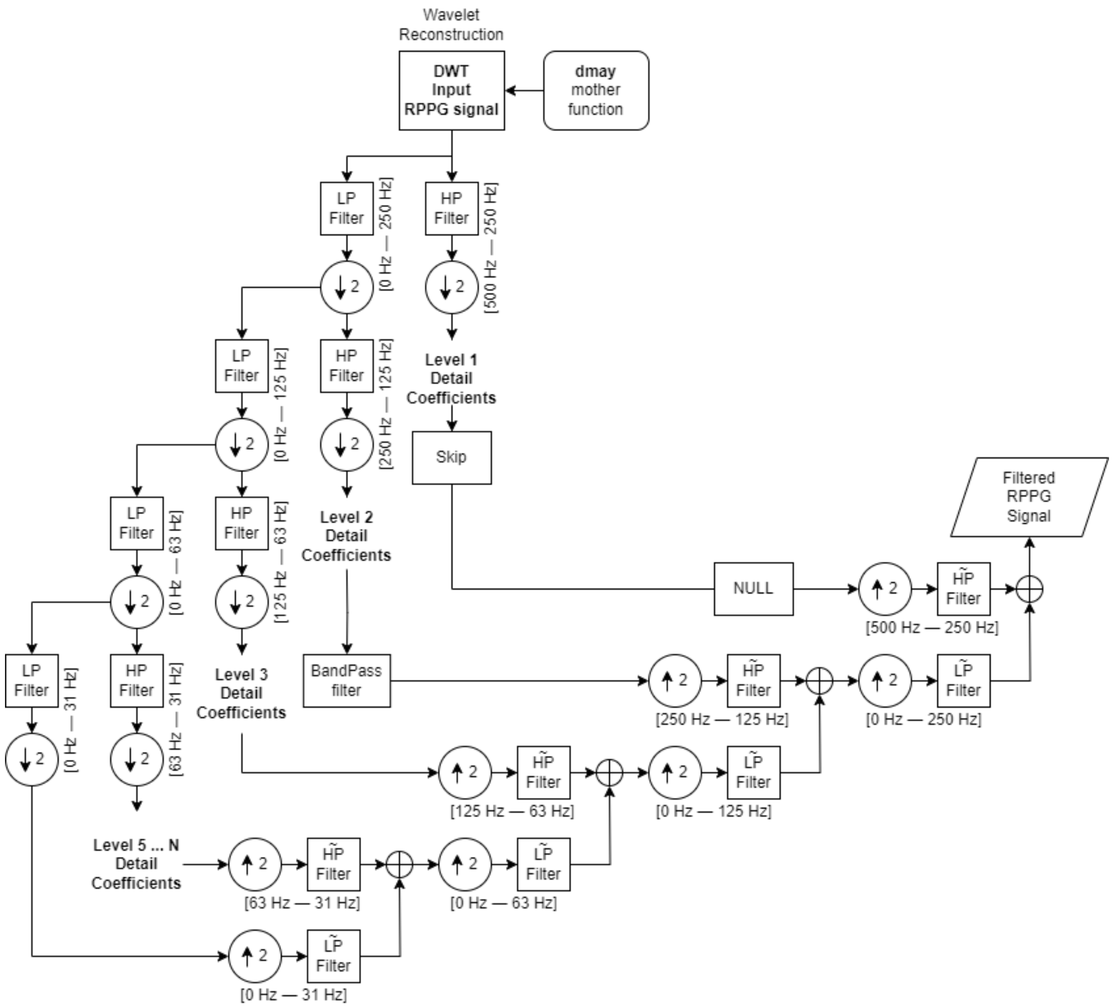

Figure 8: The general approach of multiresolution analysis of the RPPG signal

The first phase is the decomposition of the input RPPG signal into coefficients, this process is called signal deconstruction. Each pair of Low Pass (LP) and High Pass (HP) coefficients corresponds to a certain frequency range of the input signal. Having received a set of coefficients after wavelet deconstruction of the signal, frequencies with noise, such as coefficients of the 1st level of decomposition, namely in the range of 500kHz – 250kHz, are discarded. The 0Hz – 36Hz frequency and the high frequencies of 250Hz – 500Hz, where noise artifacts are present, are best filtered using wavelet filtering.

The wavelet transformation is performed using the dmey of the parent wavelet function [10]. The coefficients of the second level of decomposition should be filtered using a Bandpass filter with a setting of 0.7Hz, this will allow filtering out the interference that is present in the main signal, such as: movement in the frame, sudden changes in lighting, camera artifacts and input image artifacts. Together with the following coefficients, a set is formed that is used in the second phase. The second phase consists in reconstructing the signal using the previously calculated coefficients. The output of this scheme is the RPPG–filtered signal for further analysis and determination of cardiovascular characteristics.

The paper discusses the main elements of the remote photoplethysmography algorithm to evaluate their performance and the noise that can be generated during RGB signal compression or analysis. Noise, in turn, degrades the quality of the signal under study.

4. Experiments and results: multiresolution analysis of RPPG signal

Multi–resolution analysis of the signal after wavelet filtering and decomposition aims to display the spectrogram (Figure 9) of such a signal for the purpose of visual representation and further analysis of the RPPG signal.

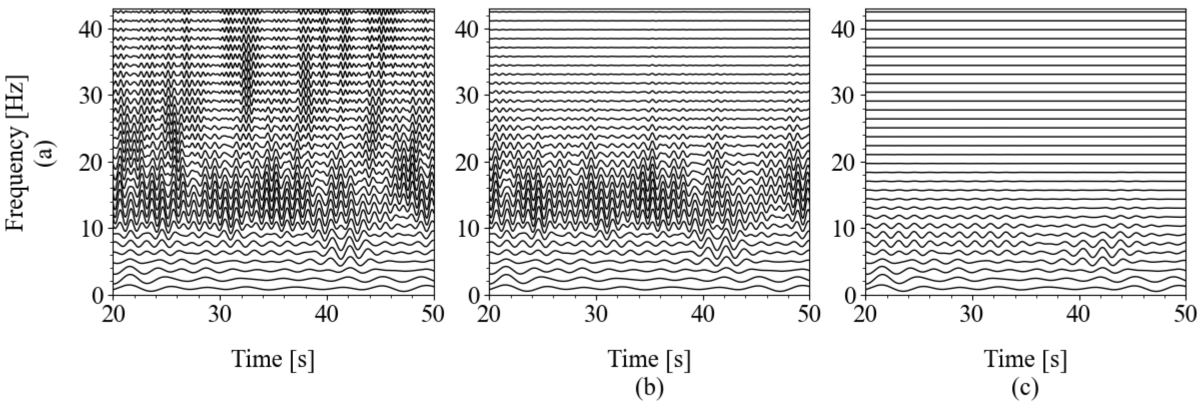

Figure 9: Spectrogram of filtered RPPG signal with various levels of CWT reconstruction: (a) CWT with reconstruction level 2, (b) CWT with reconstruction level 3, (c) CWT with reconstruction level 4

The basis of multi–resolution analysis is the result of the DWT transformation, which can be displayed using a spectrogram. Figure 10 shows the signal before filtering is applied, and Figure 11 shows the signal with wavelet filtering, using wavelet analysis and playback.

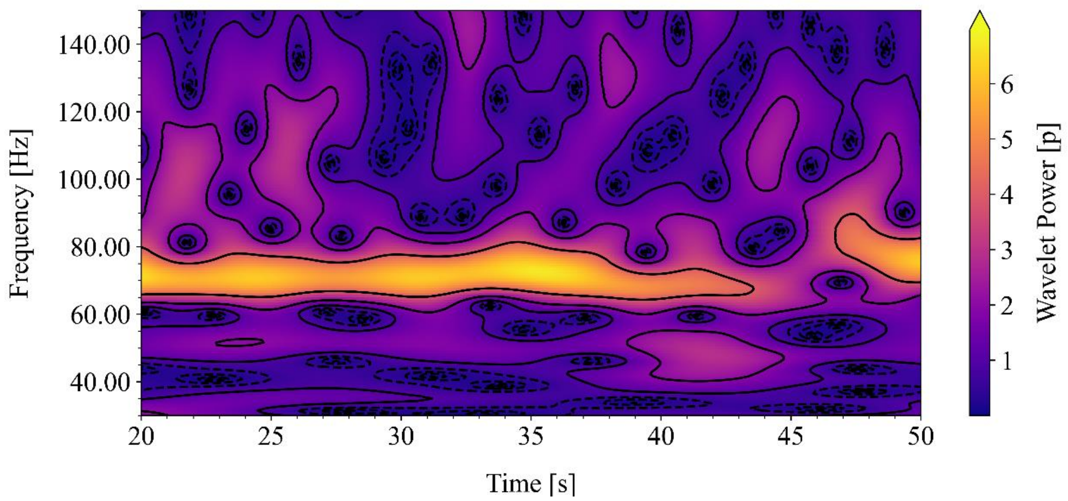

Figure 10: Spectrogram of RPPG signal

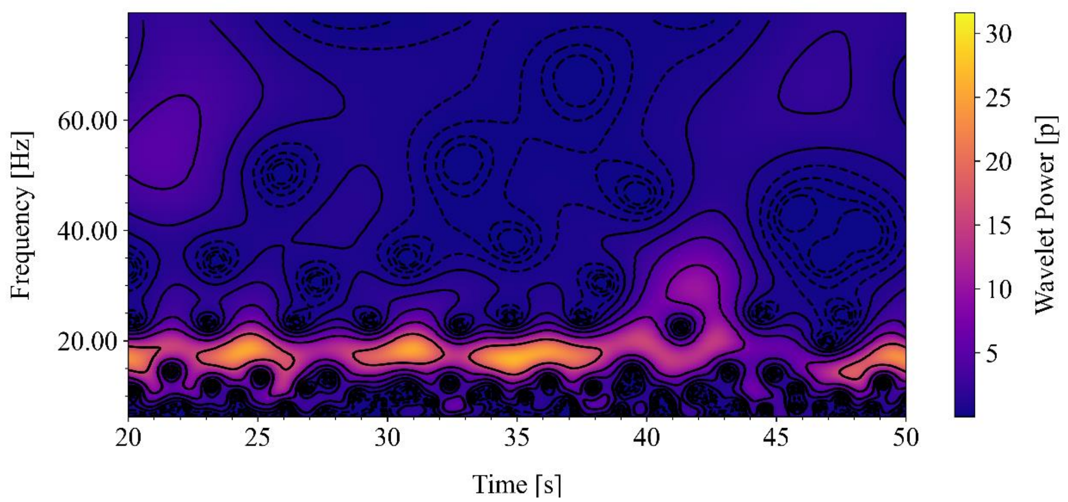

Figure 11: Spectrogram of filtered RPPG signal with 3–rd. level of CWT reconstruction

Such a representation allows evaluating the informative component of the signal and compare it with the original. The spectrogram obtained using CWT of the filtered signal is shown in Figure 12. This graph shows the signal in the time–frequency space, where there are pronounced planes with peaks that correspond to the peaks and low levels of the RPPG signal. It is worth noting that it is difficult to separate implicit signal changes, such as the dicrotic component, in such a spectrogram. Figure 13 shows the O and S components [12, 13] superimposed on the CWT spectrogram. The main informative part is present in the range of 100–300Hz. The signal containing interference and errors is located in the range of 350–500Hz and above.

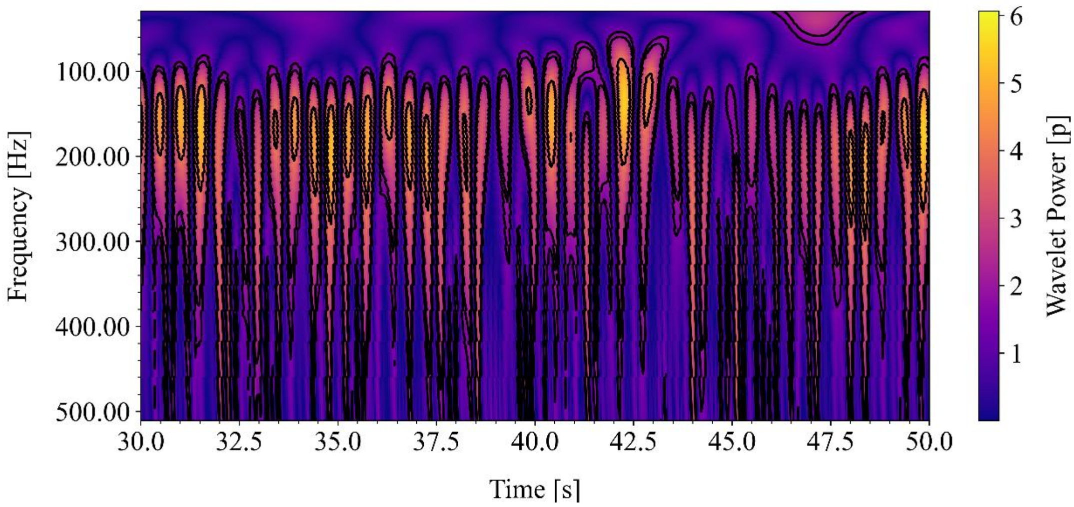

Figure 12: CWT spectrogram of filtered RPPG signal with 3–rd. level of CWT reconstruction

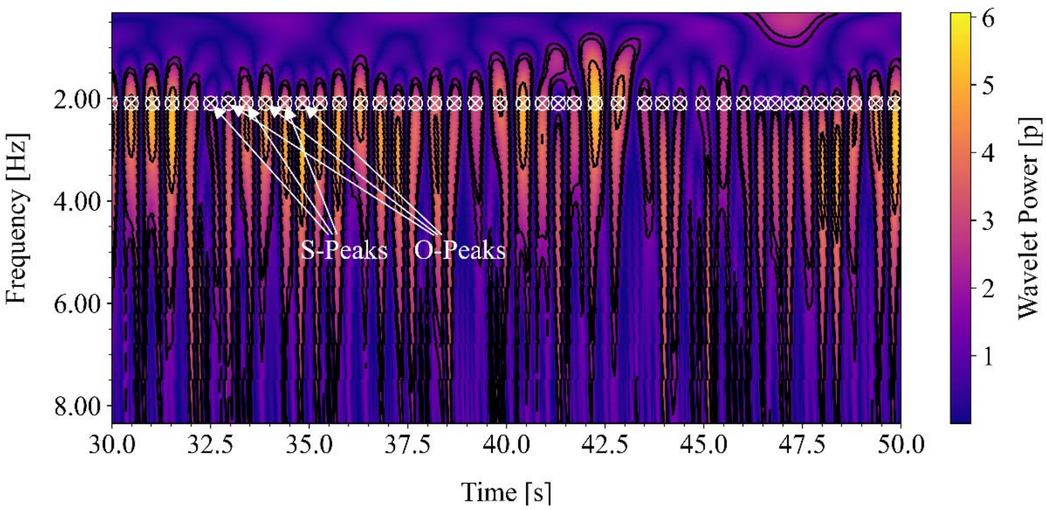

Figure 13: CWT spectrogram of filtered RPPG signal with 3–rd. level of CWT reconstruction with O and S peaks detected.

Figure 10 shows the scalogram of the signal before filtering, on which there are noises corresponding to frequencies of 90Hz - 250Hz. Also, the main RPPG signal, which is necessary for SS, is not localized, as evidenced by the large area of the signal at the frequency of 40Hz - 80Hz. Comparing the scalograms of the signals in Figure 10 and Figure 11, it can be stated that after the application of multisection filtering, the RPPG signal has a smaller signal area, and there is no noise at higher frequencies. This can also be observed in Figure 12, where the RPPG signal is displayed, namely the peaks that are necessary for CVS analysis. The correspondence of the peaks between the scalogram and the determined maxima and minima of the RPPG signal is shown in Figure 13, where you can visually confirm the correct application of the filter.

Multi–resolution analysis can be presented in the form of a graph on which informative frequencies are separated with a certain step (Figure 14). Such a graph will show the signal components after wavelet transformation, considering the step between each signal, which allows evaluating the dependencies between different signal frequencies and separate the high and low frequencies. The signal at high frequencies is visually distinguished from the signal at low frequencies by the presence of interference. Also, we can visually observe the movement of the subject in the frame between 40 and 50 seconds (Figure 15 and Figure 16).

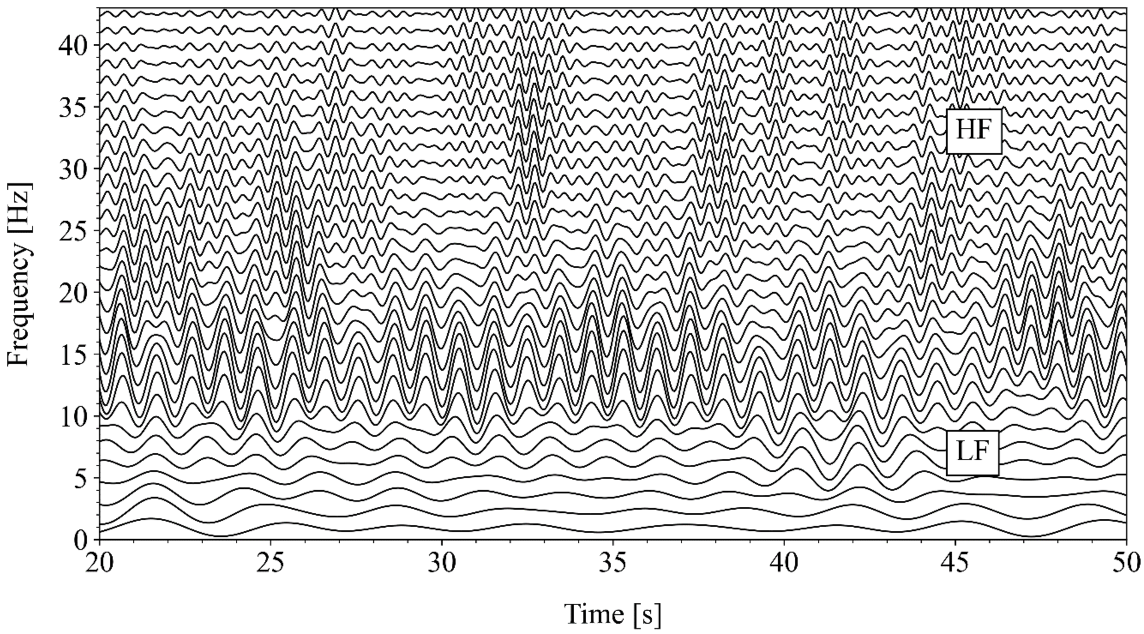

Figure 14: CWT spectrogram of filtered RPPG signal with 3–rd. level of CWT reconstruction with O and S peaks detected.

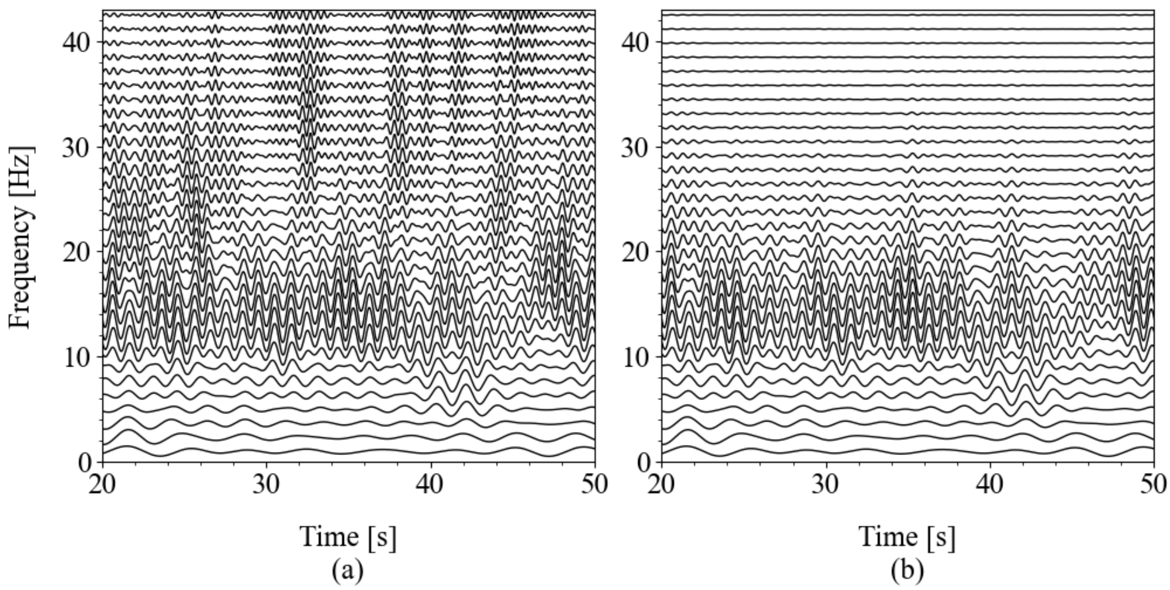

Figure 15: CWT spectrogram of filtered RPPG signal with various levels of CWT reconstruction: (a) CWT with reconstruction level 3, (b) CWT with reconstruction level 4

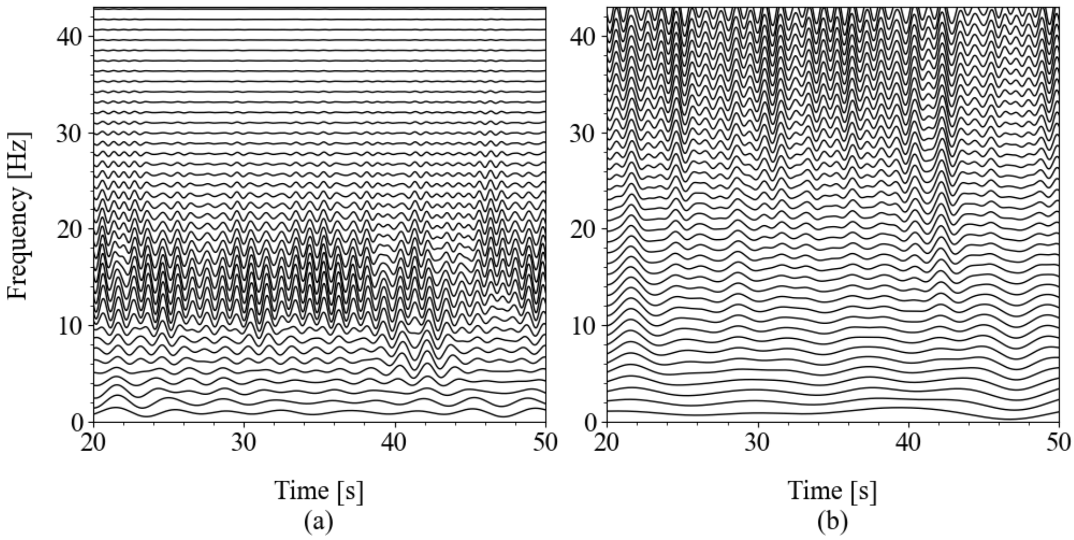

Figure 16: CWT spectrogram of filtered RPPG signal with various levels of CWT reconstruction: (a) CWT with reconstruction level 2 (b) CWT with reconstruction level 5

The results of the multiresolution analysis indicate that it is possible to obtain a clear display of the heart rate component on the RPPG signal (Figure 17). With the selected components (systolic and diastolic peaks), it is possible to analyze diseases of the human cardiovascular system. Also, these results can be interpreted as CVS variability.

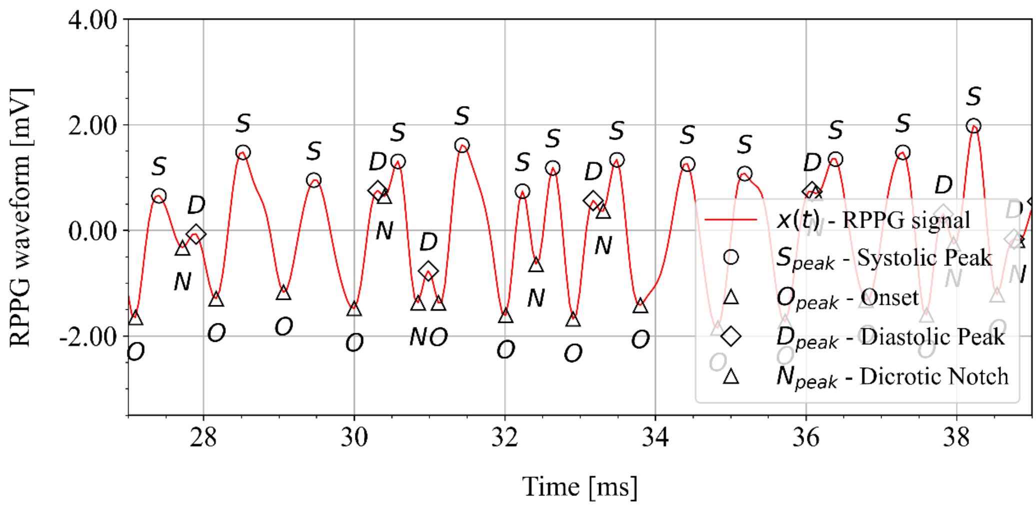

Figure 17: Result from RPPG signal after DWT reconstruction with level 3, with basic cardiac parameters

Filters perform a key role in the analysis of RPPG signals by helping to reduce noise and hence improve feature extraction and parameter estimation. This evaluation aims to thoroughly examine the various filters commonly used in RPPG analysis, identify their main steps, and evaluate their effectiveness in addressing the key requirements [14] inherent in the analysis process [14, 15] and compare them to the new multiresolution approach.

The results of the multiresolution analysis in comparison with the known approaches are presented in Table 2 and Table 3. Videos with a frame rate of 30fps or more were excluded from the analysis because the focus of the study is on signals obtained from low–quality videos. The analysis, which is commonly used for RPPG, showed that the root–mean–square error for several types of filters indicates the effectiveness of these filters for noise reduction, feature extraction, and parameter estimation (RMSE is about 1 bit/s).

Table 2
Results of multi–resolution analysis of RPPG signal on video at 15fps

Filter name	Processing	Frame per second	Performance
Bandpass Filter	Manual	15–25	RMSE: 12.5 bpm
FFT	Manual	15–25	RMSE: 8.42 bpm
ICA	Automated face tracker	15–25	RMSE: 3.81 bpm
PCA	Automated face tracker	15–25	RMSE: 4.06 bpm
Savitzky–Golay	Manual	15–25	RMSE: 3.35 bpm
Deep Learning	Manual	15–25	RMSE: 3.76 bpm
Kalman Filters	Automated face tracker	15–25	RMSE: 5.19 bpm
Multiresolution wavelet analysis	Manual	15–25	RMSE: 1.19 bpm

Table 3
Results of research for datasets with the wavelet reconstruction method for set of filters

Filter name	Dataset name	MEAN [ms]	MEDIAN [ms]	RMSSD [ms]	SD [ms]	Error [%]	Confidence [%]
Bandpass Filter	UBFC–rPPG [5]	1.329	1.326	0.456	0.511	0.451	88.87
	PURE [6]	1.237	1.248	0.468	0.49	0.567	87
	SCAMPS [7]	1.252	1.317	1.223	0.488	0.847	71.66
	UBFC–Phys [8]	1.25	1.336	0.459	0.419	0.601	79.31
	Custom (15fps)	1.245	1.258	0.39	0.458	0.493	84.34
FFT	UBFC–rPPG [5]	1.369	1.296	0.446	0.541	0.491	68.48
	PURE [6]	1.227	1.238	0.478	0.52	0.557	71.37
	SCAMPS [7]	1.322	1.257	1.223	0.498	0.857	56.12
	UBFC–Phys [8]	1.31	1.306	0.469	0.539	0.601	84.16
	Custom (15fps)	1.275	1.338	0.38	0.478	0.473	74.04
ICA and PCA	UBFC–rPPG [5]	1.299	1.316	0.396	0.501	0.481	89.89
	PURE [6]	1.197	1.248	0.488	0.51	0.527	67
	SCAMPS [7]	1.262	1.277	1.223	0.458	0.877	78.78
	UBFC–Phys [8]	1.28	1.356	0.449	0.429	0.511	92.42
	Custom (15fps)	1.305	1.218	0.41	0.478	0.453	87.37
Savitzky–Golay	UBFC–rPPG [5]	1.359	1.286	0.386	0.421	0.471	70.23
	PURE [6]	1.257	1.218	0.458	0.48	0.517	63.79
	SCAMPS [7]	1.252	1.247	1.223	0.508	0.847	50.89
	UBFC–Phys [8]	1.27	1.296	0.409	0.439	0.551	74.41
	Custom (15fps)	1.255	1.288	0.43	0.488	0.453	92.63
Multiresoluti on wavelet analysis	UBFC–rPPG [5]	1.169	1.176	0.276	0.321	0.321	85.08
	PURE [6]	1.097	1.118	0.298	0.33	0.397	87.27
	SCAMPS [7]	1.112	1.147	1.053	0.358	0.747	78.92
	UBFC–Phys [8]	1.09	1.176	0.309	0.319	0.411	89.56
	Custom (15fps)	1.135	1.118	0.28	0.328	0.313	94.54

The low RMSE values (Multiresolution wavelet analysis, Savitzky–Golay [16], Deep Learning [17]) for different filters indicate accurate signal processing, demonstrating their potential to improve the accuracy and reliability of RPPG analysis in various applications. The comprehensive RMSE evaluation provides valuable information about the performance of each filter. Overall, the RMSE analysis emphasizes the importance of robust signal processing techniques in RPPG analysis.

5. Discussion

The research project is expected to provide a system for analyzing the RPPG signal from a low-quality video stream. In order to separate the components of SS, and to design a system of diagnosis of CVS and detection of diseases. Wavelet filtering offers a versatile approach to noise suppression and feature extraction, effectively removing noise and preserving signal features at different time scales. Such adaptability is particularly useful in RPPG analysis, where signals may have dynamic and non-stationary characteristics due to physiological variations, or directly from a low-quality signal that contains many interferences caused by artifacts present in the video.

At the preliminary stages, we define specific areas and tasks, anticipating future requirements for the designed multipart RPPG signal analysis systems. The correct use and selection of basic mother functions ensures the accuracy of PPG signal reproduction [10, 11].

Multiresolution approach has been developed for the analysis of the RPPG signal obtained from a video camera of low quality and low frame rate. The approach provides a qualitative analysis of the basic components (systolic and diastolic peak, dicrotic component, heart rate, variability) of the cardiovascular system, with an accuracy of 84% to 95%. This allows the use of household cameras (mobile phones) to monitor and analyze the human cardiovascular system remotely, without using additional devices and, most importantly, to ensure non-invasiveness.

6. Conclusions and Future work

In conclusion, multiresolution approach for the analysis of the RPPG signal using multipartition CWT analysis has been developed. Which allows evaluating the variability and frequency of the heartbeat using a spectrogram. Using the datasets, the main informative section of 100-300Hz was formed for the analysis of the cardiovascular system. Defined algorithms for wavelet analysis-reproduction by wavelet transformation levels. The main information levels are highlighted, such as: levels 3 and 4 for determining R and O peaks, levels 5-6 allow for the assessment of respiratory fluctuations, levels 1-2 contain interference depending on the lack of lighting, movement in the frame or lack of frames for the assessment of the RPPG signal. Thus, the wavelet filter is an effective solution for analyzing remote photoplethysmography signals due to its versatility, reliability, and interpretability. By effectively suppressing noise and preserving signal features, the wavelet filter improves the accuracy and reliability of RPPG analysis, offering valuable information for clinical diagnosis, physiological monitoring, and scientific research. This filter reliably delivers accuracy as shown by the results from the RMSE comparison of 1.19 beats per minute. Future advances in wavelet signal processing technologies promise to further improve the efficiency and applicability of RPPG analysis in various conditions.

Prospects for further research by the authors are to further study photoplethysmographic signals, to analyze in detail the extended components of the RPPG signal to provide a reliable and accurate method for diagnosing the human cardiovascular system using signals from low–quality video cameras.

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Declaration on Generative AI

During the preparation of this work, the authors used DeepL and Grammarly in order to: Grammar and spelling check, paraphrase, reword, identify and correct grammatical errors. After using these tools, the authors reviewed and edited the content as needed and takes full responsibility for the publication’s content.

References

[1] Wang, Xin, Tapani Ahonen, and Jari Nurmi. "Applying CDMA technique to network−on−chip." IEEE transactions on very large scale integration (VLSI) systems 15.10 (2007): 1091−1100.

[2] Arslanova, I., Galvez−Pol, A., Kilner, J. et al. Seeing Through Each Other's Hearts: Inferring Others' Heart Rate as a Function of Own Heart Rate Perception and Perceived Social Intelligence. Affec Sci 3, pp. 862−877 (2022) doi:10.1007/s42761−022−00151−4

[3] L. Wang, H. Li, H. Qiu, Q. Wu, F. Meng and K. N. Ngan, "POS−Trends Dynamic−Aware Model for Video Caption," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 32, no. 7, pp. 4751−4764, July 2022, doi: 10.1109/TCSVT.2021.3131721

[4] A. Gudi, M. Bittner, R. Lochmans and J. van Gemert, "Efficient Real−Time Camera Based Estimation of Heart Rate and Its Variability," 2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW), Seoul, Korea (South), 2019, pp. 1570−1579, doi: 10.1109/ICCVW.2019.00196.

[5] Wang W, den Brinker AC, Stuijk S, de Haan G. Algorithmic Principles of Remote PPG. IEEE Trans Biomed Eng. 2017 Jul;64(7), pp. 1479−1491. doi: 10.1109/TBME.2016.2609282

[6] Serge Bobbia, Richard Macwan, Yannick Benezeth, Alamin Mansouri, and Julien Dubois. Unsupervised skin tissue segmentation for remote photoplethysmography. Pattern Recognition Letters, 124, pp. 82−90, 2019.

[7] Ronny Stricker, Steffen Müller, and Horst−Michael Gross. Non−contact video−based pulse rate measurement on a mobile service robot. In The 23rd IEEE International Symposium on Robot and Human Interactive Communication, pp. 1056−1062. IEEE, 2014.

[8] Daniel McDuff, Miah Wander, Xin Liu, Brian L Hill, Javier Hernandez, Jonathan Lester, and Tadas Baltrusaitis. Scamps: Synthetics for camera measurement of physiological signals. arXiv preprint arXiv:2206.04197, 2022.

[9] Rita Meziati Sabour, Yannick Benezeth, Pierre De Oliveira, Julien Chappe, and Fan Yang. Ubfc−phys: A multimodal database for psychophysiological studies of social stress. IEEE Transactions on Affective Computing, 2021.

[10] Nakonechnyi A., Berezhnyi I., (2023) "Estimation of heart rate and its variability based on wavelet analysis of photoplethysmographic signals in real time", Intelligent data acquisition and advanced computing systems: technology and applications: proceedings of the 12th IEEE International conference IDAACS, Dortmund, Germany, 7−9 September 2023. Vol. 1. − 2023, pp. 765−770. doi: 10.1109/IDAACS58523.2023.10348785

[11] Berezhnyi I., Nakonechnyi A., (2024). "Analysis of methods and algorithms for remote photoplethysmography signal diagnostic and filtering", Advances in Cyber−physical Systems 2024, Volume 9, Number 1, pp. 82−88, ISSN: 2524−0382, doi: 10.23939/acps2024.01.082

[12] P. Radiuk, O. Barmak, and I. Krak, "An approach to early diagnosis of pneumonia on individual radiographs based on the CNN information technology," The Open Bioinformatics Journal, vol. 14, no. 1, pp. 92−105, Jun. 2021, doi: 10.2174/1875036202114010093.

[13] Z. Cai et al., "An open−access long−term wearable ECG database for premature ventricular contractions and supraventricular premature beat detection," Journal of Medical Imaging and Health Informatics, vol. 10, no. 11, pp. 2663−2667, 2020, doi: 10.1166/jmihi.2020.3289.

[14] Hanguang Xiao, Tianqi Liu, Yisha Sun, Yulin Li, Shiyi Zhao, Alberto Avolio, (2024). "Remote photoplethysmography for heart rate measurement". Biomedical Signal Processing and Control, Volume 88, Part B, 2024, pp. 254−263, ISSN 1746−8094, doi: 10.1016/j.bspc.2023.105608.

[15] Mohammad Sabokrou, Masoud Pourreza, Xiaobai Li, Mahmood Fathy, Guoying Zhao, (2021). "Deep−HR: Fast heart rate estimation from face video under realistic conditions". Expert Systems with Applications, Volume 186, pp. 73−83, ISSN 0957−4174, doi: 10.1016/j.eswa.2021.115596.

[16] Michael Schmid, David Rath, Ulrike Diebold, (2020). "Why and How Savitzky−Golay Filters Should Be Replaced". ACS Meas. Sci. Au, pp. 185−196 doi: 10.13140/RG.2.2.20339.50725.

[17] Thayer JF, Yamamoto SS, Brosschot JF., (2010). "The relationship of autonomic imbalance, heart rate variability, and cardiovascular disease risk factors". Int J Cardiol. 2010, pp. 122−141, doi: 10.1016/j.ijcard.2009.09.543.