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Heart Rate Variability Data PPG Based Analysis

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***Abstract*— The paper presents mathematical methods for the processing and analysis of cardio data obtained by the photoplethysmographic method. Standardized linear methods (time and frequency domain) and non-linear methods (Poincaré method) were applied to study heart rate variability in two groups of recordings - of healthy people and heart disease individuals. A study was conducted to detect the relationship between the age of individuals and the values of various heart rate variability parameters. A statistical analysis was performed to determine the significance of the obtained results. The conducted analyzes show the existence of a dependence between the age of the studied population and the values of the variability parameters. The research shows the need to take diligent care of heart health as we age. A contribution in this direction is modern Information and Communication Technologies, without which people's lives today are unthinkable.**

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

I. INTRODUCTION

In recent decades, cardiovascular diseases have been among the leading causes of death worldwide. At the same time, the accelerated development of technologies makes it possible to monitor the activity of the cardiovascular system of the human body on a daily basis. To date, more and more miniature sensors are being produced that can be used to record heart activity. The small size of these sensors makes it possible to incorporate them into convenient portable devices, with which to examine important indicators such as the level of oxygen content in the blood and the level of stress (an indicator that is gaining more and more popularity in parallel with its proven utility and effectiveness for determining the health status of the person).

Photoplethysmography (PPG) offers a simple optical method for measuring and tracking heart rate. Photoplethysmography measures variations in blood volume in tissues through the use of optical sensors and is increasingly being used to monitor human health. The main advantage of this technology is that it offers a non-invasive method of measuring blood volume variations, using a light source and a photodetector located on the surface of the skin. The use of the PPG signal in heart rate estimation has been increasing in recent years. Photoplethysmography is also used to determine blood oxygen saturation, an indicator that is also important in determining human health. Mathematical analysis of heart rate variability that is extracted from the photoplethysmographic signal (also extracted from the electrocardiographic signal) can help researchers to evaluate various diseases related to the cardiovascular system and even other diseases. such as diabetes. On the basis of research on the PPG signal, the diagnosis of cardiovascular diseases can be made, the development of the heart's activity can be predicted and, on this basis, the necessary preventive measures can be taken.

Early detection of cardiovascular diseases and their monitoring in real time can be easily carried out today thanks to the latest technological discoveries in the field of sensors, which led to their miniaturization and the possibility of correct registration of the studied biomedical data.

Heart rate is a non-stationary quantity. For this reason, a suitable non-invasive method for its investigation is heart rate variability (HRV) [1,2], which takes into account the variations between adjacent heartbeats. The study of HRV makes it possible to detect heart diseases in time and to treat them appropriately. In their work [3], the authors reported increased sympathetic activity and/or decreased parasympathetic activity in patients with acute myocardial infarction. It can be concluded that heart attack patients have reduced heart rate variability, which is associated with an increased risk of adverse cardiac events and even death.

There is evidence in the scientific literature for multiple benefits of regular exercise when recommended as adjunctive therapy in patients with cardiovascular disease. Regular physical exercise can have the role of a therapeutic tool to improve the regulation of the autonomic nervous system in patients with myocardial infarction and other heart diseases. Studies have been conducted on healthy adults [4], in which the parameters of variability during intense sports loads have been investigated [5-8] and relationships between the general condition of people and symptoms of overload have been established.

However, it should be noted that there are conflicting results between individual scientific studies in this area. HRV in the field of sports medicine requires careful application and consideration of the specific characteristics of the recording device, pre-processing, analysis and careful interpretation [9]. The authors of [10-12] found that the indicators of variability are more inaccurate when conducting breathing exercises.

The purpose of this article is to present an analysis of Heart rate variability data, based on signals registered by the photoplethysmographic method.

II. PPG PRE-PROCESSING

Preprocessing of the photoplethysmographic signals is the first step that begins with the processing of the cardio signals. It aims to improve the quality of the data and make it suitable for the mathematical analysis that follows. All HRV estimation technologies are affected by noise and artifacts, so removing them from the data is mandatory. Noise is introduced by body movement in side noises. It is also necessary to detrend the baseline, interpolate the time series,

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and only then proceed to calculate the specific measures of variability in the time, frequency, and nonlinear domains.

The main steps in the preprocessing of photoplethysmographic signals usually include the following procedures:

1. Noise reduction

Photoplethysmographic signals contain various types of noise [13-15], 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.

III. Heart Rate Variability Analysis

HRV can be analyzed using different methods (linear methods - in time domain, frequency domain, time-frequency domain and non-linear methods, which can be very different, there is no standard accepted for them and they continue to develop to this day).

Types of analysis, depending on the methods used:

1. Time domain analysis

Time-domain methods quantify heart rate variability by calculating the statistical variation of R-R intervals (that is, the times from one heartbeat to the next) over a period of time.

Basic linear parameters in the time domain [16]:

SDNN (Standard Deviation of normal (NN) Intervals): Measures overall heart rate variability;

SDANN (Standard Deviation of the Average NN intervals): Reflects long-term autonomic regulation of heart rate, primarily related to slower trends like circadian rhythms or changes due to factors such as physical activity and sleep cycles;

RMSSD (Root Mean Squared Sequential Differences): Reflects short-term heart rate variability and is usually associated with parasympathetic activity:

SD ind breaks the long recording into smaller segments (usually 5-minute segments) and computes the standard deviation of NN intervals for each segment. The SD ind is the average of these standard deviations from all segments.

Time-domain analysis is standardized and often applied, especially in long-term HRV monitoring.

2. Frequency domain analysis

Frequency domain methods [17,18] analyze HRV by separating the signal into different frequency components using Fourier or wavelet transforms. These methods provide insight into how the autonomic nervous system modulates heart rate at different frequencies.

Heart rate variability is examined in the following frequency bands:

- Ultra-low frequency (ULF): < 0.003 Hz, often associated with circadian rhythms.

  ULF reflects very long-term fluctuations, including circadian rhythms and thermoregulation. It requires long recordings (typically 24 hours) to be reliably assessed.

- Very Low Frequency (VLF): 0.003–0.04 Hz, associated with thermoregulation and hormonal fluctuations.

  VLF represents longer-term regulatory processes, including influences from the renin-angiotensin system, thermoregulation, and other mechanisms that are not purely autonomic.

- Low frequency (LF): 0.04–0.15 Hz, influenced by both sympathetic and parasympathetic activity, with a slight dominance of sympathetic tone.

  LF is often associated with both sympathetic and parasympathetic activity, although it is more frequently linked with sympathetic modulation, especially during periods of stress or physical exertion.

- High Frequency (HF): 0.15–0.40 Hz, closely related to parasympathetic (vagal) activity and respiratory cycles.

  HF primarily reflects parasympathetic (vagal) activity, associated with respiratory sinus arrhythmia (the natural increase in heart rate during inhalation and decrease during exhalation). It is strongly influenced by breathing patterns.

The LF/HF ratio is often used as a measure of the balance between sympathetic and parasympathetic influences on heart rate.

3. Non-linear analysis

Nonlinear methods [19,20] provide more detailed insight into the complex behavior of the heart rate signal that cannot be captured by time and frequency domain methods.

Poincaré plot: A dot plot of R-R intervals (each interval plotted against the next) that visually represents HRV. The shape of the graph can indicate the balance between sympathetic and parasympathetic activity.

A dot plot of R-R intervals (each interval plotted against the next) that visually represents HRV. The shape of the graph can indicate the balance between sympathetic and parasympathetic activity.

A Poincaré plot [21,22] is essentially a scatterplot of successive R-wave intervals (R-R intervals) in an electrocardiogram (ECG). In the case of photoplethysmographic signals, it gives an estimate of successive P peaks (P-P intervals)

In the Poincaré diagram of each P-P interval, the following is represented:

On the x-axis: NN(i) – the current interval between two consecutive heartbeats.

On the y-axis: NN(i+1) – the next interval.

This diagram usually has an oval shape where the points are located around the diagonal line NN(i) = NN(i+1).

Main studied parameters:

SD1 (Standard Deviation 1): Short-term volatility that is perpendicular to the line of identity in the Poincaré diagram. This is the standard deviation of the scatter of points perpendicular to the line of identity (the diagonal). SD1 provides information on short-term variability, which is primarily the result of respiratory sinus arrhythmia and is directly related to parasympathetic (vagal) tone. SD1 is calculated as the standard deviation of the distances of points from the line of identity (a diagonal line where consecutive NN intervals are equal). Deviations from this line reflect variations in heart rate.

SD2 (Standard Deviation 2): Long-term volatility that is along the line of identity. This is the standard deviation of the scatter of points parallel to the line of identity. SD2 reflects the long-term fluctuations in heart rate associated with sympathetic and parasympathetic activity. SD2 is calculated as the standard deviation along the line parallel to the line of identity. This reflects long-term fluctuations in heart rate.

SD1/SD2 ratio: Gives additional information about the balance between short-term and long-term heart rate variability.

SD1 describes the short-term heart rate variability and is primarily related to parasympathetic (vagal) activity. A higher SD1 value indicates greater short-term variability, meaning a greater influence of parasympathetic tone.

SD2 describes long-term heart rate variability and reflects the balance between the sympathetic and parasympathetic nervous systems. SD2 is more related to the long-term components of the heart rate and indicates the overall level of variability.

High SD1/SD2 ratio: Indicates high short-term variability (increased parasympathetic activity), which is a sign of good health and rapid heart rate adaptation.

Low SD1/SD2 ratio: Indicates reduced short-term variability (relatively increased sympathetic activity or weaker parasympathetic control), an indicator of stress, fatigue, or other autonomic nervous system problems.

IV. RESULTS

This article presents the results of a study of 20 healthy subjects (mean age 42 years) and 24 subjects with heart disease (mean age 44 years). Half the subjects in the groups were male.

A. Time domain

Of the parameters in the time domain, the following parameters were investigated: SDNN[ms], SDANN[ms], RMSSD[ms] and SD ind[ms].

The obtained time domain results for both data types are shown in Table I.

I. TIME DOMAIN

Parameter	Healthy	Unhealthy	P value
SDNN[ms]	165.48±74.09	111.35±67.07	<0.05 (0.0149)
SDANN[ms]	142.74±68.96	102.42±43.11	<0.05 (0.0237)
RMSSD[ms]	26.32±12.65	18.02±5.18	<0.005 (0.0048)
SD ind[ms]	94.36±51.61	66.23±41.92	<0.05 (0.0499)
T test is used for statistical analysis. The P value<0.05 was considered as significant			

The parameters SDNN, SDANN, RMSSD, and SD ind were significantly lower (P value<0.05) in the records of the diseased subjects compared to the corresponding values in the healthy subjects.

B. Frequency domain

The obtained Frequency domain results for both data types are shown in Table II.

II. FREQUENCY METHOD

Parameter	Healthy	Unhealthy	P value
VLF Power [ms^2]	2823.38 ± 651.97	3055.62±831.03	0.3159
LF Power [ms^2]	1246.58±371.08	469.78±222.06	<0.0001
HF Power [ms^2]	759.03 ±344.37	383.04±136.88	<0.0001
LF Power nu	0.62±0.22	0.55±0.14	0.2076
HF Power nu	0.38±0.1	0.45±0.12	<0.05 (0.0441)
LF/HF	1.64±0.4	1.22±0.36	<0.005 (0.0007)
T test is used for statistical analysis. The P value<0.05 was considered as significant			

The obtained values for LF and HF were statistically significant. The determined values for LFnu were not statistically significant. The LF/HF ratio for healthy individuals is within the range (1.5-2.0), this is normal values for HRV. In unhealthy records, this ratio has values less than 1.5 and indicates the presence of disease and lower vital energy.

C. Poincarè Method

The obtained results are presented in Table III.

The results show statistically significant differences in two of the studied parameters (SD1 and SD2): therefore, there is a difference in the regulation of the heart. The short-term heart rate variability (measured by SD1) of healthy people (33.92 ms) was about twice the variability of non-healthy people (16.34 ms). High SD1 values in healthy people indicate good short-term HRV and a well working autonomic nervous system.

The long-term variability (measured by SD2) of healthy people (117.36 ms) was 2.25 times higher than the variability of unhealthy people (16.34 ms). High SD2 values in healthy individuals indicate stable long-term HRV and good heart rate adaptability.

The two parameters studied showed a significant decrease (P value <0.0001) in short-term and long-term HRV in heart disease patients.

No significant differences were noted in the SD1/SD2 ratio for the two types of recordings studied (P value>0.05).

III. POINCARÈ METHOD

Parameter	**Healthy**	**Unhealthy**	**P value**
SD1[ms]	33.92±12.1	16.34±8.2	<0.0001
SD2[ms]	117.36±42.13	52.11±21.36	<0.0001
SD1/SD2	0.29±0.06	0.31±0.08	0.3618

Values are expressed as mean ± standard deviation or in percent (%).
T test is used for statistical analysis.
The P value<0.05 was considered as significant

V. Discussions

PPG provides a convenient, painless and easy-to-use method for monitoring cardiac function, especially in conditions of movement or when using wearable technology. Although ECG remains the standard for heart disease diagnosis, PPG offers significant advantages for routine health monitoring and follow-up of health:

- Immediacy and convenience: PPG devices are easier to use and do not require complex electrodes. They can be integrated into wearable devices such as smartwatches and fitness trackers, making them convenient for everyday wear.
- Painless measurement: PPG does not require the application of electrodes or connection with cables, making it a painless and more pleasant method for the patient.
- Better mobility: PPG devices can be used on the go and in different environments.
- Easy integration with wearable technology: PPG is easily integrated into wearable devices, allowing continuous monitoring of heart rate and HRV during physical activity or in daily life.
- Peripheral Circulation Monitoring: PPG can provide information not only on heart rate, but also on oxygen saturation and peripheral circulation, which is useful for assessing the patient's general condition.
- Lower costs: PPG technology is usually less expensive than ECG equipment, which can be expensive and require specialized training to operate.
- Without special preparation:Unlike ECG, which may require certain conditions (eg rest before the test), PPG does not require special preparation and can be used at any time.

VI. Conclusion

Photoplethysmography is a non-invasive and inexpensive optical measurement technique applied to the surface of the skin. The main applications of photoplethyosmography are pulse oximetry and heart rate determination, from which heart rate variability is derived. In the near future, it is expected to expand the applications of PPG sensors for human health research with both preventive and prognostic purposes. When processing the PPG signal, valuable health-related information is obtained, information about the human cardiovascular system. PPG is a promising technology in both healthcare and everyday life, with its ability to determine parameters such as stress level and blood oxygen level.

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References

1. Acharya UR, Kannathal N, Sing OW, Ping LY, Chua T. Heart rate analysis in normal subjects of various age groups. Biomed Eng Online. 2004; 3: 24. doi:10.1186/1475-925X-3-24
2. Altini M, Plews D. What Is behind Changes in Resting Heart Rate and Heart Rate Variability? A Large-Scale Analysis of Longitudinal Measurements Acquired in Free-Living. Sensors. 2021; 21: 7932. doi:10.3390/s21237932
3. Nórton Luís Oliveira, Fernando Ribeiro, Alberto Jorge Alves, Madalena Teixeira, Fátima Miranda, José Oliveira, Heart rate variability in myocardial infarction patients: Effects of exercise training, Revista Portuguesa de Cardiologia, Volume 32, Issue 9, 2013, Pages 687-700, ISSN 0870-2551, https://doi.org/10.1016/j.repc.2013.02.010.
4. Kaufmann S, Gronwald T, Herold F, Hoos O. Heart Rate VariabilityDerived Thresholds for Exercise Intensity Prescription in Endurance Sports: A Systematic Review of Interrelations and Agreement with Different Ventilatory and Blood Lactate Thresholds. Sports Med Open. 2023; 9: 59. doi:10.1186/s40798- 023-00607-2
5. Bellenger CR, Fuller JT, Thomson RL, Davison K, Robertson EY, Buckley JD. Monitoring Athletic Training Status Through Autonomic Heart Rate Regulation: A Systematic Review and Meta-Analysis. Sports Med. 2016; 46: 1461-1486. doi:10.1007/s40279-016-0484-2
6. Hottenrott K, Hoos O, Esperer HD. Herzfrequenzvariabilität und Sport [Heart rate variability and physical exercise. Current status]. Herz. 2006; 31: 544-552. doi:10.1007/s00059-006-2855-1
7. Hottenrott K, Hoos O. Heart rate variability analysis in exercise physiology, in: Jelinek H, Khandoker A, Cornforth D (Eds.): ECG time series analysis: Engineering to medicine. CRC Press, London, UK. 2017: 245-257.
8. Michael S, Graham KS, Davis GM Oam. Cardiac Autonomic Responses during Exercise and Post-exercise Recovery Using Heart

Rate Variability and Systolic Time Intervals-A Review. Front Physiol. 2017; 8: 301. doi:10.3389/fphys.2017.0030

9. Gronwald T, Schaffarczyk M, Reinsberger C, Hoos O. Heart rate variability – methods and analysis in sports medicine and exercise science. Dtsch Z Sportmed. 2024; 75: 113-118. doi:10.5960/dzsm.2024.595
10. Jan, H.-Y.; Chen, M.-F.; Fu, T.-C.; Lin, W.-C.; Tsai, C.-L.; Lin, K.-P. Evaluation of Coherence between ECG and PPG Derived Parameters on Heart Rate Variability and Respiration in Healthy Volunteers with/without Controlled Breathing. *J. Med. Biol. Eng.* **2019**, *39*, 783–795.
11. Castaneda, D.; Esparza, A.; Ghamari, M.; Soltanpur, C.; Nazeran, H. A Review on Wearable Photoplethysmography Sensors and Their Potential Future Applications in Health Care. *Int. J. Biosens. Bioelectron.* **2018**, *4*, 195–202.
12. Sahroni, A.; Hassya, I.A.; Rifaldi, R.; Jannah, N.U.; Irawan, A.F.; Rahayu, A.W. HRV Assessment Using Finger-Tip Photoplethysmography (Pulserate) as Compared to ECG on Healthy Subjects during Different Postures and Fixed Breathing Pattern. *Procedia Comput. Sci.* **2019**, *161*, 535–543.
13. Kwon, J.H.; Kim, S.E.; Kim, N.H.; Lee, E.C.; Lee, J.H. Preeminently Robust Neural PPG Denoiser. *Sensors* **2022**, *22*, 2082. https://doi.org/10.3390/s22062082
14. Vraka, A.; Zangróniz, R.; Quesada, A.; Hornero, F.; Alcaraz, R.; Rieta, J.J. A Novel Signal Restoration Method of Noisy Photoplethysmograms for Uninterrupted Health Monitoring. *Sensors* **2024**, *24*, 141. https://doi.org/10.3390/s24010141
15. George R.E. Bradley, Panayiotis A. Kyriacou, Opening the envelope: Efficient envelope-based PPG denoising algorithm, Biomedical Signal Processing and Control, Volume 88, Part A, 2024, 105693, ISSN 1746-8094, https://doi.org/10.1016/j.bspc.2023.105693.
16. Pineda-Alpizar, F.; Arriola-Valverde, S.; Vado-Chacón, M.; Sossa-Rojas, D.; Liu, H.; Zheng, D. Real-Time Evaluation of Time-Domain Pulse Rate Variability Parameters in Different Postures and Breathing Patterns Using Wireless Photoplethysmography Sensor: Towards Remote Healthcare in Low-Resource Communities. *Sensors* **2023**, *23*, 4246. https://doi.org/10.3390/s23094246
17. Garbilis, A.; Mednieks, J. Differences in Heart Rate Variability in the Frequency Domain between Different Groups of Patients. *Medicina* **2024**, *60*, 900. https://doi.org/10.3390/medicina60060900
18. Kiselev, A.R.; Posnenkova, O.M.; Karavaev, A.S.; Shvartz, V.A.; Novikov, M.Y.; Gridnev, V.I. Frequency-Domain Features and Low-Frequency Synchronization of Photoplethysmographic Waveform Variability and Heart Rate Variability with Increasing Severity of Cardiovascular Diseases. *Biomedicines* **2024**, *12*, 2088. https://doi.org/10.3390/biomedicines12092088
19. Milena, Č.; Romano, C.; De Tommasi, F.; Carassiti, M.; Formica, D.; Schena, E.; Massaroni, C. Linear and Non-Linear Heart Rate Variability Indexes from Heart-Induced Mechanical Signals Recorded with a Skin-Interfaced IMU. *Sensors* **2023**, *23*, 1615. https://doi.org/10.3390/s23031615
20. Calderón-Juárez, M.; Cruz-Vega, I.B.; González-Gómez, G.H.; Lerma, C. Nonlinear Dynamics of Heart Rate Variability after Acutely Induced Myocardial Ischemia by Percutaneous Transluminal Coronary Angioplasty. *Entropy* **2023**, *25*, 469. https://doi.org/10.3390/e25030469
21. D'Addio, G.; Donisi, L.; Cesarelli, G.; Amitrano, F.; Coccia, A.; La Rovere, M.T.; Ricciardi, C. Extracting Features from Poincaré Plots to Distinguish Congestive Heart Failure Patients According to NYHA Classes. *Bioengineering* **2021**, *8*, 138. https://doi.org/10.3390/bioengineering8100138
22. Donisi, L.; Ricciardi, C.; Cesarelli, G.; Coccia, A.; Amitrano, F.; Adamo, S.; D'Addio, G. Bidimensional and Tridimensional Poincaré Maps in Cardiology: A Multiclass Machine Learning Study. *Electronics* **2022**, *11*, 448. https://doi.org/10.3390/electronics11030448