Complex Control Systems
ISSN 1310-8255 **Proceedings of the International Scientific Conference "Robotics & Mechatronics 2023"**

Cardiological signal processing and analysis methods

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***Abstract*— The paper presents tools for analyzing cardiac data using heart rate variability methods. Linear and non-linear methods are presented for the analysis of heart rate variability, which is a dynamic, non-stationary variable. Analysis of heart rate with mathematical methods is a topical issue. Electrocardiography and long-term Holter recordings have established themselves as non-invasive medical assessment methods cardiovascular activity. In the time domain, the parameters established in practice are defined. Spectral analysis of heart rate variability makes it possible to evaluate the work of the heart and evaluate its status in the coming days. Spectral analysis is usually performed in three frequency bands and can to be done with different mathematical methods. Analyzes were performed on real long-term Holter files for patients with proven heart disease diagnosed by a cardiologist and for persons without cardiovascular problems. The presented numerical and graphical results were obtained using of the software program in a Visual Studio environment. Comparative analyzes showed differences in the frequency studied parameters between heart disease patients and healthy individuals. The studies carried out and the obtained results may be useful in the clinical practice of cardiologists.**

***Keywords* — Cardiovascular diseases, ECG, heart rate variability, Holter, PPG.**

I. INTRODUCTION

Cardiovascular research diseases carried out in the past years, show a connection between the activity of the heart and the work of the autonomic nervous system [1]. The studies on the cardiovascular system are performed through cardio recordings, registered mainly in three ways: with electrocardiograph, photoplethysmographic device or holter [2, 3].

Heart rate variability (HRV) represents the change in time of successive heart beats, and this phenomenon is closely related to the regulation of the autonomic nervous system. Scientific research [4, 5] shows a close relationship between cardiovascular disease and the interaction between the sympathetic and parasympathetic nervous systems. Thus, heart rate variability is formed over time as an indicator [6] of the health of the human body.

HRV is also beginning to be used in clinical practice as research shows that a number of disease states depend on changes in the intervals between heartbeats [7-9].

The work of various researchers over the years has proven increased incidence of both total mortality and cardiac events occurred as in apparently healthy middle-aged and elderly people; which have reduced heart rate variability. Decreased HRV is a reflection of increased sympathetic activity [10]. Decreased parasympathetic or sympathetic tone overstimulation leads to a decrease in HRV and lowers the threshold for the origin of different type's arrhythmias, some of which can be life-threatening [11].

In the scientific literature, there is evidence of a relationship between the tendency to have lethal arrhythmias and increased sympathetic or decreased vagal activity.

This leads to increased development efforts quantitative markers of autonomic activity. HRV has the potential to deliver additional insight into the conditions induced from impaired cardiovascular activity [1]. Heart rate variability today is one of the markers of autonomous activity. HRV can be described such as variations of RR intervals and instantaneous heart rate [12]. The basis for heart rate variability as a measure of autonomic modulation is that the parasympathetic branch of the autonomic nervous system (ANS) has a very rapid tissue response and rapid recovery from neural stimulation, allowing high frequency of neural activity. The sympathetic nervous system (SNS) has a low frequency of nervous activity, as there is a very slow onset of tissue reaction and recovery from nerve stimulation. Primarily the parasympathetic control of the heart results in large variations in heart rate due to the rapid onset and restoration of the parasympathetic system.

II. STATISTICAL PARAMETERS IN THE TIME DOMAIN

Methods for measuring autonomic activity in the time domain are the simplest to implement. In these methods, determines the heart rate at any point in time, the intervals between them separate consecutive heartbeats are determined. In a continuous electrocardiographic (ECG) recording, each QRS (Q, R, S - main points in the electrocardiogram) complex is detected as well. In this way, the time series of RR intervals is created.

Then the so-called normal-to-normal (NN) intervals (ie, all intervals between adjacent QRS complexes resulting from the depolarization of the sinus node). The current heart rate is also determined.

In this paper the following Statistical parameters were studied [1, 13]:

- SDNN [ms] – Standard deviation of the average duration of all NN; reflects the overall variability:

$$SDNN = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(RR_i - \overline{RR})} \quad (1)$$

- SDANN [ms] – Standard deviation of the average NN in the blocks of five min data, to which the series is divided:

$$SDANN = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\overline{RR_i} - \overline{\overline{RR}})^2} \quad (2)$$

- SDNN index [ms] – Average of all NN for the blocks of 5 min data of the whole record:

$$SDNN_{index} = \frac{1}{N}\sum_{i=N}^{N} SDNN_i \quad (3)$$

- RMSSD [ms] – The standard deviation of the intervals between successive heartbeats; reflects the activity of parasympathetic:

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - \overline{RR_i})^2} \quad (4)$$

- NN50 [-] – The number of adjacent pairs of normal-to-normal intervals with a difference of more than fifty milliseconds, across the record:

$$NN50 = \sum_{i=1}^{N}\{|RR_{i+1} - RR_i| > 50ms\} \quad (5)$$

- pNN50 [%] – NN50 divided by the number of normal intervals:

$$pNN50 = \frac{NN50}{N}.100 \quad (6)$$

- SDSD [ms] – Standard deviation of differences between adjacent N-N intervals:

$$SDSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}\left(|RR_i - RR_{i+1}| - \overline{RRdif}\right)^2}$$

Where:

N- count of all intervals in the segment;

$\overline{\mathrm{RR}} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{RR_i}$ - average of all RR intervals,

$\overline{RR_i}$ - average of RR intervals in the segment,

$\overline{\overline{\mathrm{RR}}} = \frac{1}{\mathrm{M}}\sum_{\mathrm{i=1}}^{\mathrm{M}} \mathrm{RR_i}$ - mean of all mean RR intervals in all 5 min segments (M per count),

$$\overline{RRdif} = \frac{1}{N-1}\sum_{i=i}^{N}\left(|RR_i - RR_{i+1}|\right) \quad (7)$$

III. PARAMETERS IN THE FREQUENCY DOMAIN

Spectral methods measure the variation of signal power as a function of frequency. The classic method in the frequency domain is the calculation of the Discrete Fourier Transform and Fast Fourier Transform applied to the interval time series. This gives an expression of the amount of variation in the individual frequency bands.

In this study, the global wavelet spectrum is determined for the following three frequency ranges:

- VLF (Very Low Frequency) – from 0.0033 to 0.04 Hz;
- LF (Low Frequency) – from 0.04 Hz to 0.15 Hz;
- HF (High Frequency) – from 0.15 Hz to 0.4 Hz.

Determination in these areas is done using the following dependencies [14]:

$$EVLF = Ew(6) + Ewt(7); \quad (8)$$

$$ELF = Ew(5) + Ewt(4); \quad (9)$$

$$EHF = Ew(1) + Ewt(2) + Ewt(3). \quad (10)$$

Where:

$Ew(i)$ - the spectral wavelet energy at the i-th level of Decomposition.

IV. NON-LINEAR PARAMETERS

Poincaré plot analysis [15, 16] is a non-linear geometric name for assessing HRV dynamics. This method draws a diagram in which each RR interval is plotted as a function of the previous RR interval. The values of each pair of consecutive RR intervals define a point on the diagram. Through this graphical tool, the RR time series can be visualized in a two-dimensional coordinate system. As the main indicators, the minor (SD1) and major axis (SD2) of the formed ellipse [15] is widely used to evaluate the morphology of the time series, which two axes represent the short-term and long-term HRV, respectively.

In the present study, the classical form of the Poincaré graph is drawn and the two axes of the resulting ellipse are determined.

The graph provides summary information as well as detailed information about the behavior of the heart. Previous studies have focused on the change in the spectral components of HRV during the onset of illness. However, the Poincaré plot of HRV and the possible effects of different events have not been well studied. Using Poincaré plot analysis may be a better way to monitor the dynamic change of autonomic nervous system and its impact on cardiac activity.

V. RESULTS AND ANALYSIS

The presented tabular results are obtained as a result of a purpose-built C++ program in Microsoft Visual Studio environment.

The studies were made on HRV time series derived from real cardio data. The type of RR intervals of a studied patient with cardiovascular disease is shown in Fig. 1. The graph shows 16 hours and 40 minutes of continuous record registrated with Holter monitoring. Almost throughout the recording time, the variability of adjacent intervals is not large, and cardiac variability parameters have average values.

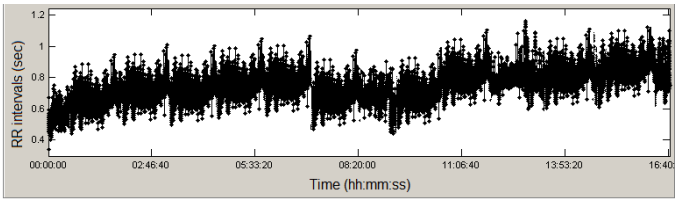
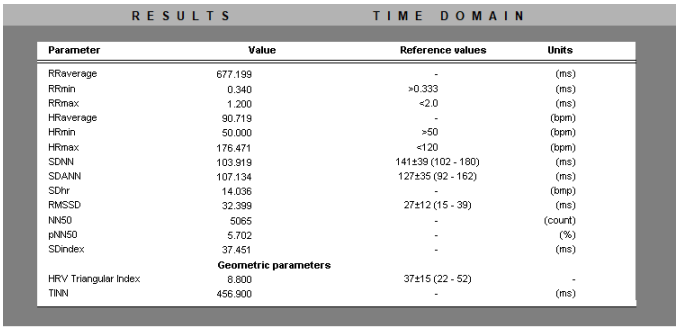


Fig. 1. RR intervals

Figure 2 shows the results obtained in the time domain and is the result of the action of the created demonstrative program (one of its result fields).


RESULTS TIME DOMAIN

Parameter	Value	Reference values	Units
RRaverage	677.199	-	(ms)
RRmin	0.340	>0.333	(ms)
RRmax	1.200	<2.0	(ms)
HRaverage	90.719	-	(bpm)
HRmin	50.000	>50	(bpm)
HRmax	176.471	<120	(bpm)
SDNN	103.919	141±39 (102 - 180)	(ms)
SDANN	107.134	127±35 (92 - 162)	(ms)
SDhr	14.036	-	(bmp)
RMSSD	32.399	27±12 (15 - 39)	(ms)
NN50	5065	-	(count)
pNN50	5.702	-	(%)
SDindex	37.451	-	(ms)
Geometric parameters			
HRV Triangular Index	8.800	37±15 (22 - 52)	-
TINN	456.900	-	(ms)

Fig. 2. Time domain

Table 1 presents the results of studies of records of healthy people (N=12) and people with cardiovascular problems (diagnosed with past syncope, N=12). A T-test was performed to determine the significance of the obtained results. Significant significance of the results is accepted at values of the parameter p-value<0.05.

Table 1. Results time domain

Parameter	**Heathy mean±sd**	**Syncope mean±sd**	**p-value**
Mean RR (ms)	838.82 ±142	882.73±65	NS
SDNN (ms)	138.1±61	82.44±25	<0.01
SDANN (ms)	144.66±53	61.99±33	<0.0001
SDNN index (ms)	52.33±22	32.8±13	<0.05
RMSSD (ms)	24.12±46	12.68±7	<0.05
pNN50	5.7±1.02	6.4±1.01	NS
SDSD	16.08±2.1	18.09±3.2	NS

The determined parameters in the time domain and the calculated p-values indicate that the parameters

SDNN, SDANN, SDNN index, RMSSD are statistically significant (P-value<0.05). For example, SDNN has a mean value of 144ms in healthy subjects versus only a 61ms mean value in syncope subjects (P-value <0.0001).

The spectral parameters in the frequency domain are calculated for a 5 minute segment of the data (in accordance with the recommendations of the European Cardiology and Northern American Electrophysiological Society [1]).

Wavelet analysis of heart rate variability by discrete wavelet transformation is performed by frequency ranges. The wavelet energies were calculated the coefficients by decomposition levels, according to the wavelet determination rule energy spectrum defined as the sum of the squares of the positive values of the corresponding wavelet coefficients. The calculated energy by levels of decomposition of a record from a real database (with cardiovascular disease) is shown in Table 2. The performed analysis reports the highest spectral energy at level three and level four, in these levels the QRS complex is most strongly reflected, which has the highest amplitude at the R peak.

Table 2. Energy by decomposition levels

Level of decomposition	Spectral energy (ms^2)
1	0.112
2	18.77
3	64.12
4	32.24
5	11.45
6	8.99
7	14.04

The calculated energy values in the three frequency ranges for the two studied groups are given in Table 3. The obtained results are presented as an average value ± standard deviation (sd). The energy in the individual ranges in is presented absolute values (ms^2), in percentages (of the total) and in normal units (n.u.), which represent the relative value of each energy component to the total spectral energy minus the value of the VLF component. The ratio was also calculated LF/HF, giving information about the sympathovagal balance in the body.

The studies done in the frequency domain show increased values of the spectrum of the studied signal in the very low frequencies in the recordings made with Holter of heart disease patients. In the low-frequency and high-frequency regions, the opposite trend is observed: decreased levels of the signal Power spectrum in both investigated regions in patients with cardiovascular diseases. These differences are observed both for the measured signal Power spectrum in absolute units and in percentages and in normalized units. For example, the signal power in a healthy person averaged 1286 ms for the LF region versus 648 ms in a person with heart disease; in the high-frequency region absolute spectral power 812 ms^2 versus 622 ms^2 mean value of absolute spectral power in human syncope.

In general, the following conclusion is imposed: the indicators of heart rate variability in the low-frequency and high-frequency region are decreased in the studied ECG records of people with cardiovascular diseases compared to healthy people.

Table 3. Energy by frequency ranges.

Parameters	Healthy N=8	Heart Disease N=8	P value
VLF			
Max freq.	0.02	0.02	NS
Power (ms^2)	1438± 304.22	2031±876.73	NS
Power (%)	0.41± 0.03	0.61± 0.02	<0.05
LF			
Max freq.	0.08	0.08	NS
Power (ms^2)	1286.48± 102.73	648.22±36.91	<0.05
Power (%)	0.36±0.02	0.20±0.01	<0.05
Power (nu)	0.61±0.06	0.51±0.01	<0.05
HF			
Max freq.	0.25	0.25	NS
Power (ms^2)	812.33± 104.06	622.73±103.88	<0.05
Power (%)	0.23±0.02	0.19±0.02	NS
Power (nu)	0.39±0.08	0.49±0.02	<0.05
LF/HF	1.58±0.01	1.04±0.03	<0.05

In Fig. 3. the standard Poincaré plot for an individual diagnosed with syncope is shown. SD1 and SD2 are the minor axes and the major axes of the fitted ellipse. The defined parameters for this record are SD1=22.9 ms and SD2=145.2 ms. The graph has an irregular shape, which indicates the irregular nature of the studied time series. From the determined values for SD1 and SD2, it can be concluded that the studied record has low short-term HR variability and relatively high long-term HR variability.

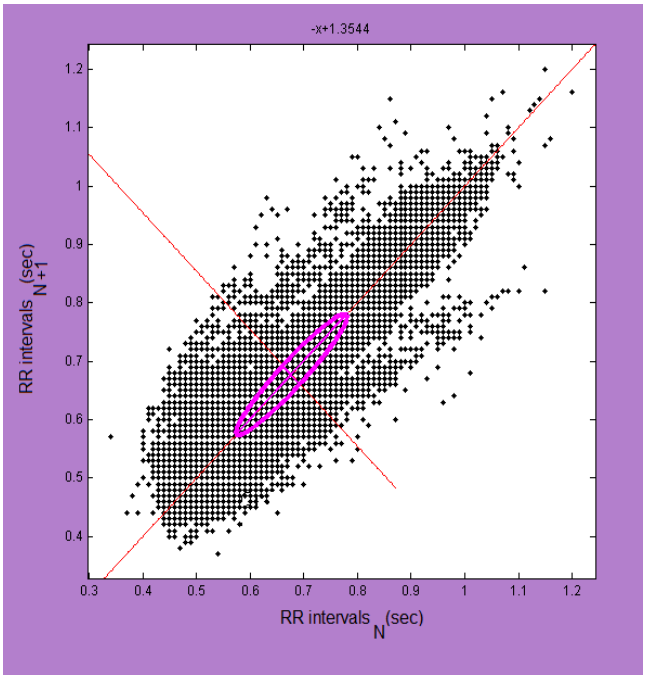


Fig. 3. Poincaré plot

VI. Conclusion

The article presents linear and non-linear algorithms for the analysis of cardiac data, estimating heart rate variability. Analyzes were performed on real continuous Holter recordings which are non-invasive methods of assessing heart activity. The presented methods are complete analysis in the time and frequency domain and determine evaluation parameters. The analyzes are performed on records for patients with heart disease diagnosed by cardiologist and for people without cardiovascular disease. The presented numerical and graphical results were obtained using the software program in a visual studio environment.

Comparative analyzes show differences in the studied frequency parameters between patients with heart disease and healthy individuals. The research conducted and the obtained results can be used to improve clinical practice of cardiologists.

Acknowledgments

The study was carried out as part of a scientific project "Research on the application of new mathematical methods for the analysis of cardiac data" financed by the Bulgarian National Science Fund, Grant No. KP-06-N22/5, 7 December 2018.

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