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Effect of Body Posture on Heart Rate Variability Analysis of ECG Signal

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Abstract— **An assessment of cardiac function derived from the ECG signal is known as heart charge variability (HRV). The evaluation of HRV provides ways for analyzing entry into the heart rhythm non-invasively, which can be used to guide treatment. For the prevailing study, records of ten members in two one-of-a-kind frame postures have been taken. Sets of records have been received in sleeping and sitting positions. In addition, The R-peak produced from the ECG is employed in the evaluation of the RR interval. It is also applied for the evaluation of HRV. In the context of coronary heart rate (HR), HRV is linked to tachycardia (HR > 100 bpm) and bradycardia (HR 60 bpm). Linear HRV characteristics with unique time-domain and frequency-domain indices are interpreted into two distinct postures. As a result, it is possible to conclude that the RR interval increases for the supine position during all two poses, as sitting appears to be a more comfortable situation than the alternative one. Also, as the frequency-area evaluation result proposes, the LF/HF ratio is better in the supine position, i.e., better sympathetic has an effect. Consequently, supine has a higher resting circumstance than that sitting. A non-linear Poincare plot has also been incorporated for accessing variability.**

Keywords- Electrocardiogram (ECG), Heart rate, RR interval, Poincare plot, Heart rate variability (HRV).

I. INTRODUCTION

An electrocardiogram (ECG) is an electric signal produced by the coronary heart. During a typical cardiac cycle, the electric impulse drives the human coronary heart muscle tissues to compress and relax, pumping blood from the coronary heart [1]. Non-invasive biomedical applications include HR estimation, cardiac rhythm monitoring, emotion detection, biometric identity, and coronary heart abnormalities diagnosis, among others, based on the ECG signal's quasi-periodic behavior.

ECG indications can be recorded by placing Ag-AgCl electrodes in defined locations on the human body, such as the chest, arms, and legs [2]. It can also be recorded on ECG paper using 12 lead electrodes containing precordial lead placed on the chest wall. An electrocardiogram (ECG) is a test that measures electrical activity in the heart. ECG measures the heartbeat rate and rhythms, whether they are steady or erratic [3].

The ECG sample of the same person changes with time and with the health of the individual. [4]. The ECG signals standard beat, seen in Figure 1, contains the P wave, the PQ portion, the QRS wave, the ST section, and the T wave. It outlines how functions are represented using amplitude and time intervals (msecs) and amplitudes (mv). A P wave takes place because of atrial depolarization. The AV delay is indicated by the PQ section, which is an isoelectric line. Because QRS is complicated because of ventricular depolarization, which may every so often have an effect via means of conduction disease, The ST segment is an isoelectric line that is in perfect harmony with the PQ section, and ventricular repolarization of the heart results in T wave [6,7].

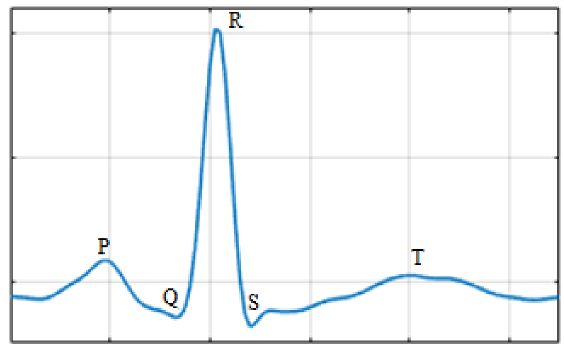

Figure 1. ECG Beat

In comparison to supine and sitting, standing posture shows a much lower HRV value representing vagal activity and a significantly higher sympathetic activity [8, 9]. Resting HRV measurements, including SDNN and RMSSD, show more variability in the supine position than the upright posture. Different non-linear HRV indices like long-term variability SD1, long-term variability SD2, and ratio SD2/SD1 for balance between long-time period variability and short-time period variability were interpreted in one-of-a-kind frame postures, and it was concluded that supine posture has a decrease in SD1/SD2 ratio than sitting, and supine indicates a decrease in SD1/SD2 ratio, representing better variability [10].

In the present investigation, linear, in addition to non-linear HRV analysis, paying attention to the RR interval, has been investigated for two one-of-a-kind frame postures, particularly supine and sitting. And comparative evaluation for the RR intervals and HRV measures is being proven within the result section.

The remainder of this work is divided into sections II, III, IV, and V, with sections II, III, IV, and V devoted to methods, HRV analysis, results and discussion, and conclusion, respectively.

II. METHODS

A. Participants

Five healthy males and the same number of healthy females totaling ten participants of the age group 19-26 years (Mean ± SEM: 21.7±1.69) and 90% CI as 19.87-23.34 have been considered for the present investigation.

B. Data Processing

The ECG signal has a favorable frequency range of 0.5–45 Hz [11]. Other than that, certain frequency degrees are treated as noise in the ECG signal since they diminish HR and HRV estimate prognostication and diagnostics.

Electromagnetic interference from power supply lines occurs at a frequency of 50 Hz on cables transmitting ECG signals. PLI is considered high frequency based on the ECG signal's usable frequency range. An FFT notch filter can be used to eliminate this problem.

Baseline Wander is a low-frequency noise that is caused mainly by breathing and muscular activity. This work makes use of wavelet-based ECG noise reduction techniques, as indicated in [12]. The signal is decomposed using tenth-level wavelet decomposition, resulting in noise. The filtered signal is obtained by subtracting it from the preprocessed signal using a notch filter. Glitches are reduced using an average filter to improve the effectiveness of peak identification of the ECG signal. Figure 2 shows the original ECG signal as well as the filtered ECG signal.

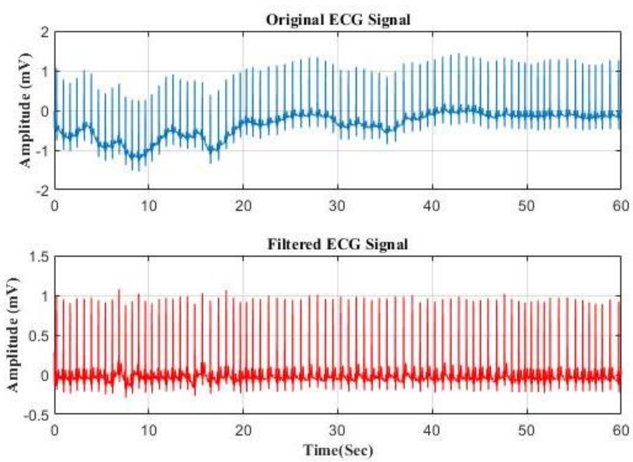

Figure 2. Original and Filtered ECG Signal

Detection of R-peak is now possible with the filtered signal. It was decided to employ the closest neighbor technique and set the threshold at 45% of the highest possible peak values. R-peak detection is also possible with maximum overlap discrete wavelet transform, as mentioned in [13]. The R-peak of each QRS complex has been detected to achieve the successive RR interval.

III. HRV ANALYSIS

An HRV analysis in the time domain is a statistical metric that is based on the RR interval. The following table lists the various time-domain HRV parameters [13].

- ***RR:*** The average of all RR intervals.
- ***SDANN:*** The average NN interval's standard deviation during a brief period.
- ***RMSSD:*** Root mean square (RMS) of the RR interval's successive difference,
- ***SDSD:*** stands for the square root of the successive difference in the square of the RR interval.
- ***pNN50:*** The proportion of NN pairings that are longer than 50 msec.

Area per unit energy and power spectral density curves are used in the frequency domain HRV study. It provides an overview of how power is distributed across frequency bands. The high frequency (HF) component provides a quantitative measure of vagal cardiac function, whereas the low frequency (LF) component measures the influence of sympathetic nerves. As a result, the ratio LF/HF is a good indicator of sympathovagal interaction [14].

In non-linear HRV analysis, a statistical method known as beat-to-beat or NN beats is used to measure the heart rate variability. Short-term variability (SD1) and long-term variability (SD2) are calculated from the Poincare Plot, which is a wide range of graphical representations of numerical data of successive RR intervals. SD2/SD1 is the measure of balance among long-term and short-term variability.

IV. RESULTS AND DISCUSSION

RR intervals are obtained from the filtered signal for both postural conditions, i.e., supine and sitting. The mean RR interval for each participant, along with their mean and standard deviation values (Mean±SD), are shown in Table I. It represents the mean values of RR interval for each participant and has higher values for supine than for sitting. The RR bar plot has been shown in Figure 3.

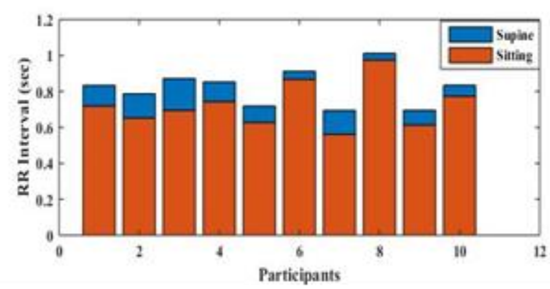

Figure 3. RR Bar Plot (Supine Vs Sitting)

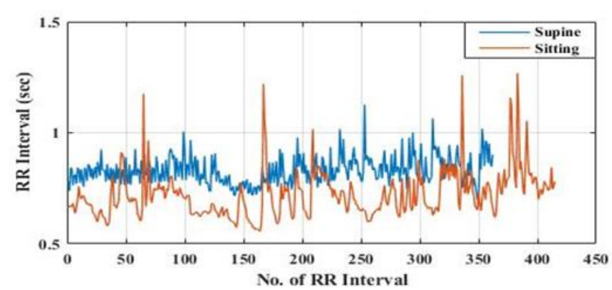

Figure 4. A Number of the RR Intervals in Supine Vs. Sitting for Individual

The number of peak positions for the person is shown in Figure 4. From Figure 4, it can be analyzed that for the 5 min ECG data, the number of RR intervals for sitting is higher than that of supine as supine has higher resting RR interval than sitting. According to the literature [15], these deviations are due to the displacement of blood from the central body to the lower body region, affecting cardiac activity.

TABLE I. MEAN RR INTERVAL IN SUPINE AND SITTING POSTURE

	Participants	1	2	3	4	5	6	7	8	9	10	Mean±SD
RR Interval (sec)	Supine	0.834	0.787	0.872	0.853	0.719	0.912	0.694	1.012	0.695	0.835	**0.821±0.101**
	Sitting	0.719	0.652	0.694	0.743	0.627	0.867	0.561	0.974	0.613	0.773	**0.722±0.125**

TABLE II. LINEAR HRV PARAMETERS

	Participants	1	2	3	4	5	6	7	8	9	10	Mean±SD
Time-Domain Analysis												
SDNN (msec)	Sitting	40.81	34.86	28.82	56.84	30.21	47.41	15.74	67.08	26.37	31.45	**37.95±15.37**
	Supine	46.89	45.92	73.76	59.35	29.02	50.29	28.02	92.67	38.59	44.47	**50.91±19.93**
Mean HR	Sitting	84.29	92.54	89.61	80.19	99.61	78.34	107.44	67.97	99.31	75.68	**87.49±12.39**
	Supine	72.42	76.94	70.35	71.25	90.57	69.22	91.73	61.17	87.56	72.14	**76.33±10.22**
RMSSD (msec)	Sitting	40.98	27.21	21.04	47.29	19.46	31.07	8.15	94.64	20.13	44.16	**35.41±24.22**
	Supine	74.97	49.15	89.48	67.76	29.31	56.93	23.42	169.61	28.24	77.25	**66.61±42.74**
pNN50 (%)	Sitting	24.67	5.19	6.08	37.95	2.85	29.54	0	37.20	13.41	14.57	**17.15±14.26**
	Supine	46.23	25.78	59.61	45.59	1.71	34.66	0	54.76	16.17	29.25	**31.37±20.84**
Frequency-Domain Analysis												
LFnu	Sitting	65.09	77.43	62.34	52.71	59.13	71.25	77.24	49.07	65.32	64.16	**64.37±9.35**
	Supine	38.28	53.28	21.65	39.42	64.79	41.39	71.65	36.13	61.81	34.66	**46.31±15.83**
HFnu	Sitting	31.24	25.64	39.65	66.16	41.36	29.16	23.60	63.82	31.54	31.53	**37.37±15.05**
	Supine	54.49	49.37	91.18	71.55	56.16	55.15	25.23	52.47	39.15	62.31	**55.70±17.66**
LF/HF	Sitting	2.21	3.01	1.57	0.79	1.43	2.44	3.27	0.77	2.07	2.03	**1.96±0.84**
	Supine	0.70	1.08	0.24	0.55	1.15	0.75	2.84	0.69	1.58	0.56	**1.04±0.74**

Table II shows linear HRV parameters in time and frequency domains for each participant, along with their mean and SD. The mean RR interval decreases, and the HR increases as the body posture change from supine to sitting in a resting position, as seen in the preceding data. In supine posture, RMSSD and the pNN50 have a higher value than sitting. The LF/HF ratio in the frequency domain is higher in the sitting posture than in the supine posture, indicating that LF power content is higher in the sitting posture than in the supine posture, and least for the analysis, indicating that supine posture has a more substantial sympathetic influence.

Figure 5 shows the Poincare plot, a sequential difference of the RR intervals, for individuals in both body positions, supine and seated. Using the Poincare plot, SD1 and SD2 have been estimated with the use of elliptical fitting techniques using the Kubios HRV 3.2 software. As a result, the following outcomes are revealed in Table III.

TABLE III. NON-LINEAR HRV PARAMETER

	Participants	I	II	III	IV	V	VI	VII	VIII	IX	X	Mean±SD
SD1	Sitting	56.17	27.84	19.18	41.61	19.77	32.15	24.06	79.65	24.37	26.65	**35.16±19.23**
	Supine	48.18	39.83	71.24	48.19	18.72	42.34	19.49	97.13	29.01	32.94	**44.70±24.04**
SD2	Sitting	97.13	49.34	33.35	64.81	41.85	64.92	34.47	87.48	39.96	46.42	**55.97±22.14**
	Supine	47.33	58.19	71.52	56.18	43.22	55.49	28.89	102.36	42.68	52.43	**55.83±19.88**
SD2/SD1	Sitting	1.73	1.73	1.77	1.74	2.12	2.02	1.43	1.09	1.63	1.74	**1.70±0.29**
	Supine	0.88	0.98	1.46	1.01	2.31	1.31	1.48	1.05	1.47	1.59	**1.35±0.42**

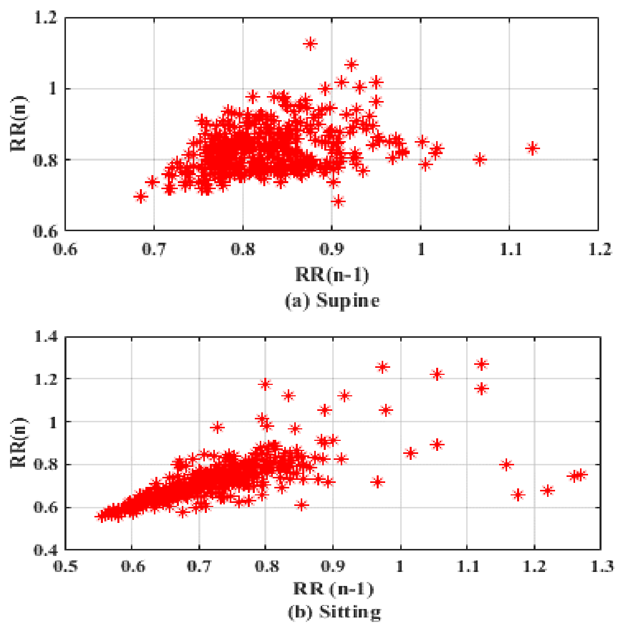

Figure 5. Poincare Plot (A) Supine (B) Sitting

The data shows that supine posture has a reduced SD2/SD1 ratio than sitting posture. The smaller the SD2/SD1, the more fluctuation there will be. i.e., supine is more variable than seated posture.

V. Conclusion

Information about cardiac responses may be gleaned not just from HRV measures but also from those taken in the time and frequency domains. HRV components in ECG signals are correlated with HR fluctuations. Various linear HRV parameters for two body positions, especially sitting and supine, are presented in this work. Sitting posture is associated with a lower RR interval and a higher resting HR than the supine position. In comparison to the sitting position, the supine position had higher RMSSD, SDNN NN50, and pNN50 values. In terms of frequency-domain characteristics, the LF/HF ratio indicates that the supine position has a more substantial sympathetic influence than the seated posture. The results of non-linear HRV indices also show that supine body position has more variability than seated body posture. Furthermore, for a better understanding, the current study might be expanded to include prone and tilt body postures.

References

[1] Alberdi, A. Aztiria and A. Basarab, "Towards an automatic early stress recognition system for office environments based on multimodal measurements: A review", Journal of Biomedical Informatics, vol. 59, pp. 49–75, 2016.

[2] M. Abo-Zahhad, "ECG signal compression using discrete wavelet transform—Theory and applications", Discrete Wavelet Transform, pp. 143–168, April 2011.

[3] Mohamed Hammad, Asmaa Maher, Kuanquan Wang, Feng Jiang, and Moussa Amrani, "Detection of abnormal heart conditions based on characteristics of ECG signals", Measurement, vol 125, pp. 634-644, September 2018.

[4] W. Jiang and S.G. Kong, "Block-Based neural networks for personalized ECG signal classification", IEEE Transactions Neural Network, vol 18(6), pp. 1750–1761, November 2007.

[5] S.Z. Mahmoodabadi, A. Ahmadian, and M.D. Abolhasani, "ECG feature extraction using Daubechies wavelets", International Conference Visualization, Imaging and Image Processing, pp. 343- 348, Benidorm, September 2005.

[6] I. Odinaka, L. Po-Hsiang, A.D. Kaplan, J.A. O'Sullivan, E.J. Sirevaag and J.W. Rohrbaugh, "ECG biometric recognition: A comparative analysis", IEEE Transactions Information Forensics Security, vol 7(6), pp. 1812–1823, December 2012.

[7] Inderbir Kaur, Rajni Rajni, and Anupma Marwaha, "ECG signal analysis and arrhythmia detection using wavelet transform", Journal of The Institution of Engineers (India), vol 9(4), pp.499-507, December 2016.

[8] Prashant Kumar, Ashis Kumar Das, Prachita, Suman Halder, "Time-domain HRV Analysis of ECG Signal under Different Body Postures", Procedia Computer Science, Vol. 167, pp. 1705-1710, 2020.

[9] G Banskota Nepal and BH Paudel, "Effect of posture on heart rate variability in schoolchildren." Nepal Medical College Journal, 14(4): 298-302, 2012.

[10] Prashant Kumar, Ashis Kr. Das and Suman Halder. (2020) Non-linear Heart Rate Variability Analysis of Electrocardiogram Signal Under Different Body Posture. In: Dawn S., Balas V., Esposito A., Gope S. (eds) Intelligent Techniques and Applications in Science and Technology. ICIMSAT 2019. Learning and Analytics in Intelligent Systems, vol 12. Springer, Cham. https://doi.org/10.1007/978-3-030-42363-6_115

[11] Ahsan Habib Khandoker, Chandan Karmakar, Michael Brennan, Marimuthu Palaniswami and Andreas Voss. (2003) "Poincaré plot methods for heart rate variability analysis." in Springer Publication.

[12] S.K. Yadav, R. Sinha, and P.K. Bora, "Electrocardiogram signal denoising using non-local wavelet transform domain filtering", IET Signal Processing, vol. 9, pp. 88–96, December 2015.

[13] Prashant Kumar, Ashis Kr. Das and Suman Halder, 'Statistical heart rate variability analysis under rest and post-exercise, International Journal of Computational Science and Engineering, vol. 25(2), pp.186–197, 2022.

[14] K. K Tripathi., "Respiration and heart rate variability: A review with special reference to its application in aerospace medicine." Indian Journal of Aerospace Medicine, vol. 48(1): pp. 64-75, 2004.

[15] Sanhita Rajan Walawalkar, "A study of variation in heart rate variability with change in posture in young adult Indian males" Journal of Medical Science and Clinical Research, vol. 2(3), pp. 503-514, 2014.

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