Fundamental Considerations while Developing Real-Time Heart Rate Variability Biofeedback Systems

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Abstract

Heart rate variability (HRV) biofeedback training is known for its effectiveness in improving physical health, emotional health, and resilience by the ability to regulate heart rhythm. However, there are various challenges in delivering and interpreting the biofeedback information which prevents an optimal experience. This study presents the fundamentals of developing a real-time HRV biofeedback system using deep breathing exercise by exploring the minimum time window of RR-intervals resulting in a reliable analysis. Moreover, it investigates the appropriate HRV measures by examining the significant changes between resting and breathing conditions and the trends consistency across different time segments. The overall results suggest that a minimum time window of 20-second can provide a reliable HRV time–domain analysis. Whereas the possible HRV measures that can be used in the real–time biofeedback system are SDNN, LF, LF/HF, and total power.

1. Introduction

The biofeedback discipline has emerged from the intersection of psychology and medicine to treat mental and physical diseases. As the term implies, the conceptual meaning is *"feeding back"* biological information to the user in order to involuntarily regulate the physiological activities and body's functioning [1]. Ostensibly, the feedback information is displayed via external interfaces such as visual, audio, or haptics. One of the prevalent biofeedback approaches is devoted to regulating cardiac activity by generating RR oscillations with a sinusoidal-like waveform representing the instantaneous heart rate. More specifically, the increase and decrease of HRV are accompanied by breathing where inhalation and exhalation activate sympathetic and parasympathetic nervous systems, respectively [2].

Over the last few decades, heart rate variability (HRV) has become a vital non–invasive indicator of state of health, reflecting the balance of the autonomic nervous system [3]. HRV is determined by the time interval between two consecutive heartbeats, with a lower value of HRV (less variations in the heartbeats) implying that a person suffers from stress, mental or physical disease. In HRV biofeedback, the ultimate aim is to maximise the oscillations of HRV, which can be achieved by following slow breathing rate exercises. Commonly, the rate at which the HRV reaches the maximum is called resonant frequency (RF). Lehrer et al. [4] proposed a resonance breathing protocol to train participants on HRV biofeedback technique in multiple sessions. This protocol has been widely used by researchers to investigate the long-term impact of HRV biofeedback on physical and cognitive performance.

Therefore, in this paper we seek to establish a case for the feasibility of deploying an advanced real–time HRV biofeedback system for self–monitoring to improve health and wellbeing.

The hypotheses of this study are as follows:

Hypothesis 1 (H1): Ultra-short-term analysis can provide reliable measures to monitor the sympathetic and parasympathetic activities during deep breathing exercise.

Hypothesis 2 (H2): The range of values of HRV measures during deep breathing exercise differ from baseline while individuals are in a resting state and they are consistent across short time segments.

2. Background

The growing demand for improving the mental health status of individuals, along with the recent development of wearable technologies brought the attention of real–time health monitoring systems. This would provide new approaches to take immediate actions and/or avoid certain events from occurring. As discussed earlier, HRV is a good indication for stress levels and physical health; however, a minimum window of 5-minutes does not conform to real–time requirements. Therefore, researchers investigated the reliability of ultra-short-term analysis (i.e. segments of less than 5-minutes) in the context of assessing mental stress levels [5, 6]. For instance, Munoz et al. [7] carried out a thorough validity test for ultra-short-term analysis of segments with duration of 2-min, 30-seconds, and

Table 1: Multilevel linear model analysis

Feature	5 min		2 min		1 min		30 sec		20 sec		10 sec	
	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p	χ^2	p
MeanNN	31.40	.00	25.77	.00	26.93	.00	26.07	.00	38.37	.00	27.5	.00
SDNN	12.84	.00	10.55	.01	9.374	.03	10.49	.01	9.88	.02	24.18	.00
RMSSD	3.59	.31	2.95	.40	1.78	.62	2.05	.56	4.14	.25	2.3	.07
PNN50	6.94	.07	2.97	.40	1.2	.75	1.59	.66	1.27	.74	6.95	.07
HF	1.24	.74	3.62	.31	1.86	.60	1.30	.73	2.65	.45	2.01	.07
LF	41.43	.00	35.07	.00	30.44	.00	29.75	.00	15.13	.00	19.21	.00
Total Pow	37.14	.00	27.39	.00	26.71	.00	17.42	.00	10.06	.02	8.936	.03
LF/HF	16.10	.00	17.11	.00	17.22	.00	17.32	.00	12.2	.01	19.52	.00

10-seconds using correlation test, Bland-Altman analysis, and Cohen's d. At a three averaged 10-seconds segment, they achieved high correlation coefficients with the standard 5-minute intervals (r=.86 for SDNN, and r=.94 for RMSSD). However, this study was limited to RMSSD and SDNN measures only from time-domain during a resting condition.

Castaldo et al. [8] followed the reported guidelines in [9] and discussed the results of time-domain, frequency-domain, and non-linear measures in 3-min, 2-min, 1-min, and 30-seconds during rest and stressed phases to be used in an auto-detect stress classifier. They found that MeanNN, SDNN, HF, and SD2 presented a great consistency across all shorter segments and a high correlation with the 5-minute recordings. In the 30-second segments, the computation of some of the HRV measures, such as LF, HF and LF/HF, lead to erroneous values due to the insufficient number of samples. In fact, Malik et al. [10] pointed out that for spectral analysis, the length of the segment should be ten times the wavelength of the lower bound frequency of the investigated spectral band. For example, to obtain a reliable analysis for HF power (frequency band: 0.15—0.4 Hz), the minimum length should be around 1 minute; calculated as $10 \times \frac{1}{0.15} \approx 66$ seconds. Nevertheless, Yu et al. [11] used real–time HRV analysis in the context of biofeedback with a window of 16 beats including a full respiratory cycle; the sampling rate was 500 Hz.

3. Methods

3.1. Experiment design

A controlled experiment was designed to collect short-term HRV recordings using PPG-based sensor device. There were three different conditions: 1) at rest as a baseline measurement, 2) during mentally stressed task, and 3) during deep breathing as a post-stress recovery exercise. After the data collection, the HRV recordings passed through three main stages, including signal filtering, segmentation, and HRV analysis as in Figure 1. Each RR recording was divided into shorter time segments of 120, 60, 30, 20, 10 seconds. To assess the reliability of ultra-short-term analysis (<5 min), the HRV measures of each segment were compared to the standard 5 minutes as a benchmark using Pearson's correlation test. Also, the statistical test of the multilevel linear model and Tukey posthoc analysis were performed to evaluate the appropriate HRV measures representing the influence of deep breathing on RR recordings and ensuring the trends consistency across shorter segments with the benchmark.

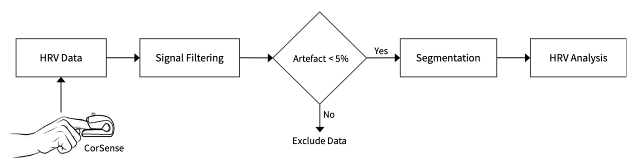


Figure 1: High-level architecture of the experimental study

3.2. Procedure

The experiment sessions were conducted in the daytime over several days from 9:30 am to 12:30 pm, where each session lasted for 35 minutes. The experimental study consisted of collecting HRV under 1) a controlled condition to establish a baseline measurement, where the participants instructed to sit quietly and breath naturally for six minutes, 2) a mental stress task based on on the Trier Social Stress protocol [12] with a duration of 15 minutes, and 3) a post-stress activity. During the stress task, the participants had 5 minutes to mentally prepare for the speaking task without taking written notes, then 5 minutes to deliver the speech. The last 5 minutes were dedicated for the mental arithmetic task, in which they were asked to subtract 13 from 1022 sequentially. The post-stress activity was mainly a deep breathing exercise for six minutes, which aimed to reduce the stress by regulating the heart rate and increasing the HRV. The participants were asked to breathe at a rate of 7 breaths per minute with the same inhale/exhale ratio by following an illustrative guide of opening and closing a circle from a mobile-based deep breathing application.

3.3. Participants

The HRV data of 20 healthy participants (age range: 20-36 years) from Queen Mary University of London were included in the experimental analysis. Out of them, 11 were male (mean age: 27.6+-4.3), and 9 were female (mean age: 27.9+-2.2). To minimise any external factors that may affect the measurements of the cardiac activity, the participants were informed to avoid alcohol, coffee, heavy meals, and intensive workouts for the last 24 hours prior to the experiment [13]. Also, a questionnaire was provided to the participants asking about their physical health, fitness level, sleeping routine, and alcohol/coffee intake as recommended by [14]. All participants were informed about the nature of the experiment and signed a written consent form.

4. Results

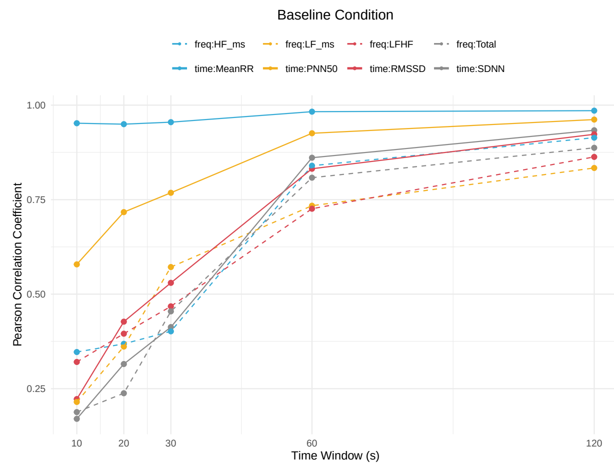
4.1. Reliability of ultra-short-term analysis

Pearson correlation test was used to assess the reliability of ultra-short-term analysis in baseline and deep breathing conditions. Since the RR intervals in slow-paced breathing tend to be a periodic signal, we hypothesised the correlation is higher in shorter segments as compared to the other conditions. From Figure 2, it can be noticed that all HRV measures in the breathing condition maintained a higher significant relationship with the 5-min recording in contrast with the baseline. For instance, in the 2-min segments, none of the measures scored less than 90% in breathing, whereas the lowest score in the baseline was 83% for the LF power. At the 20s segment, the SDNN could account for at least 77% of the variation in SDNN at the 5-minute segment (r=.88). Despite the drop for all HRV features after 30s segment, the MeanNN maintained a significant relationship for the 20s and 10s segments.

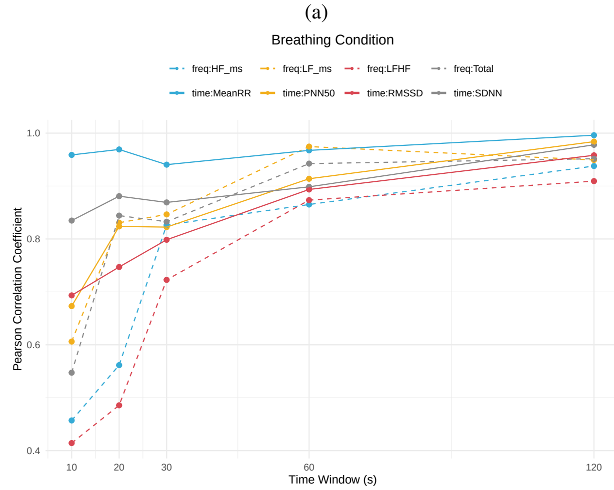
4.2. Influence of deep breathing on HRV

The results of the multilevel linear analysis for the 5-minute recordings is summarised in 1. It can be observed that MeanNN and SDNN from the time domain had a significant effect at 5% (all p-values$<$.05) across all time segments. Tukey posthoc analysis revealed that SDNN measure was significantly higher during deep breathing exercise as compared with the baseline measurements.

Concerning the frequency domain measures, LF, LF/HF, and total power had a significant effect (all p-values$<$.05) across the different five-time scales. The results of Tukey posthoc analysis showed a significant increase in the spectral domain in the breathing condition as compared with the baseline.



(a)



(b)

Figure 2: Correlation across all time segments in baseline and breathing conditions

The trend of the average HRV features during the deep breathing activity was investigated on each time segment. Table 2 summarises the results where the arrows

Overall, SDNN, LF, LF/HF, and total power significantly increased in the deep breathing condition, and they were consistent across all time-scales. Although, the MeanNN had a significant decrease from resting to stress states, it increased during deep breathing and reached a value that's close to the baseline.

5. Conclusions and Future Work

In summary, the most appropriate HRV measure for slow paced-breathing are SDNN and LF power attributes.

Table 2: Trend Analysis

Feature	Breathing 300	120	60	30	20	10
MeanNN	$\approx$	$\approx$	$\approx$	$\approx$	$\uparrow$	$\uparrow$
SDNN	$\upuparrows$	$\upuparrows$	$\upuparrows$	$\upuparrows$	$\upuparrows$	$\uparrow$
RMSSD	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\upuparrows$
PNN50	$\uparrow$	$\uparrow$	$\approx$	$\approx$	$\uparrow$	$\uparrow$
HF Power	$\approx$	$\approx$	$\approx$	$\uparrow$	$\uparrow$	$\upuparrows$
LF Power	$\upuparrows$	$\upuparrows$	$\upuparrows$	$\upuparrows$	$\upuparrows$	$\upuparrows$
LF/HF	$\upuparrows$	$\upuparrows$	$\upuparrows$	$\upuparrows$	$\upuparrows$	$\upuparrows$
TotalPow	$\upuparrows$	$\upuparrows$	$\upuparrows$	$\upuparrows$	$\upuparrows$	$\upuparrows$

($\uparrow$, $\downarrow$) indicates the direction of the change from the baseline
($\upuparrows$, $\downdownarrows$) indicates the significance of the change
($\approx$) indicates there was no change in the state as compared to the baseline.

This can be combined with the instantaneous RR intervals to provide more insights about the balance of the autonomic nervous system. Also, one important design constraint is the shortest reliable time window for the HRV analysis. From this study, it can be concluded that the shortest time segment that can be used is 20-second for time domain analysis. However, it is important to ensure the inclusion of 1 breathing cycle for the frequency domain analysis; thus a 30-second segment is preferable. The outcomes of this study will contribute to design a self-monitoring HRV biofeedback system based on developing multi-modal displays, including visual, audio or haptics.

Acknowledgements

This study was made possible by grant QRLP10-G-1803029 from the Qatar National Research Fund (a member of Qatar Foundation).

References

[1] Brown BB. Stress and the Art of Biofeedback. Harper Row 1977;.

[2] Khazan IZ. The Clinical Handbook of Biofeedback. Chichester, UK: John Wiley & Sons, Ltd, 4 2013. ISBN 9781118485309.

[3] Billman GE. Heart rate variability - A historical perspective. Frontiers in Physiology 2011;2 NOV(November):1–13. ISSN 1664042X.

[4] Lehrer P, Vaschillo B, Zucker T, Graves J, Katsamanis M, Aviles M, Wamboldt F. Protocol for Heart Rate Variability Biofeedback Training. Biofeedback 2013;41(3):98–109. ISSN 1081-5937.

[5] Baek HJ, Cho CH, Cho J, Woo JM. Reliability of ultra-short-term analysis as a surrogate of standard 5-min analysis of heart rate variability. Telemedicine and e Health 2015; 21(5):404–414. ISSN 15563669.

[6] Salahuddin L, Cho J, Jeong MG, Kim D. Ultra short term analysis of heart rate variability for monitoring mental stress in mobile settings. Annual International Conference of the IEEE Engineering in Medicine and Biology Proceedings 2007;ISSN 05891019.

[7] Munoz ML, Van Roon A, Riese H, Thio C, Oostenbroek E, Westrik I, De Geus EJ, Gansevoort R, Lefrandt J, Nolte IM, Snieder H. Validity of (Ultra-)Short recordings for heart rate variability measurements. PLoS ONE 2015;10(9):1–15. ISSN 19326203.

[8] Castaldo R, Montesinos L, Melillo P, James C, Pecchia L. Ultra-short term HRV features as surrogates of short term HRV: A case study on mental stress detection in real life. BMC Medical Informatics and Decision Making 2019; 19(1):1–13. ISSN 14726947.

[9] Pecchia L, Castaldo R, Montesinos L, Melillo P. Are ultra-short heart rate variability features good surrogates of short-term ones? State-of-the-art review and recommendations. Healthcare Technology Letters 2018;5(3):94–100. ISSN 20533713.

[10] Malik M, Bigger JT, Camm AJ, Kleiger RE, Malliani A, Moss AJ, Schwartz PJ. Heart rate variability: Standards of measurement, physiological interpretation, and clinical use. European Heart Journal 3 1996;17(3):354–381. ISSN 0195-668X.

[11] Yu B, Funk M, Hu J, Feijs L. Unwind: a musical biofeedback for relaxation assistance. Behaviour and Information Technology 2018;37(8):800–814. ISSN 13623001.

[12] Kirschbaum C, Pirke KM, Hellhammer DH. The 'Trier social stress test' - A tool for investigating psychobiological stress responses in a laboratory setting. Neuropsychobiology 1993;28(1-2):76–81. ISSN 0302282X.

[13] Laborde S, Mosley E, Thayer JF. Heart rate variability and cardiac vagal tone in psychophysiological research - Recommendations for experiment planning, data analysis, and data reporting. Frontiers in Psychology 2017;8(FEB):1–18. ISSN 16641078.

[14] Quintana DS, Alvares GA, Heathers JA. Guidelines for Reporting Articles on Psychiatry and Heart rate variability (GRAPH): recommendations to advance research communication. Translational psychiatry 2016;6(5):e803. ISSN 21583188. URL `http://dx.doi.org/10.1038/tp.2016.73`.