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Validation of the Happify Breather Biofeedback Exercise to Track Heart Rate Variability Using an Optical Sensor

Purpose of the Study: The goal of the current experiments was to determine whether the optical/PPG sensor used in the Breather app using a smartphone camera can yield accurate heart rate signals by comparing results with simultaneously obtained Holter acquiring ECG signals. There were two trials. In the first, no automatic detection of finger presence or movement was included in the Breather algorithm. In the second, detection of finger presence/movement was included in the signal generated by the app.

Methods:

Experiment 1. N=40 one-minute segments were obtained in 3 volunteers who wore a DMS myPatch Holter monitor (Figure 1) while repeatedly testing the Breather app on an IPhone 6. The Breather app uses a PPG (i.e., polyplethysmography) sensor (1). The IPhone flash was illuminated, and the changes in the red color signal from the finger, which was pressed to the lens of the IPhone camera were sampled at 50 Hz. The red color in the finger varies with blood flow, increasing with systole and decreasing on diastole, and therefore was expected to be a surrogate for the instantaneous heart rate signal. Subjects were instructed to breathe at 6 cycles/min, following cues from the application. The sampled signal data from the

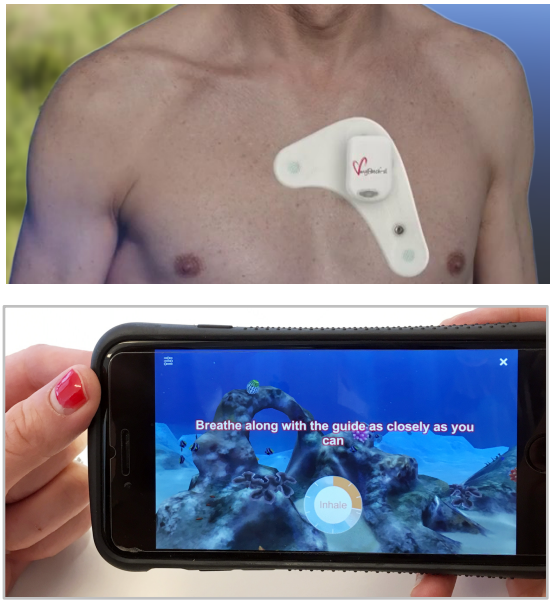
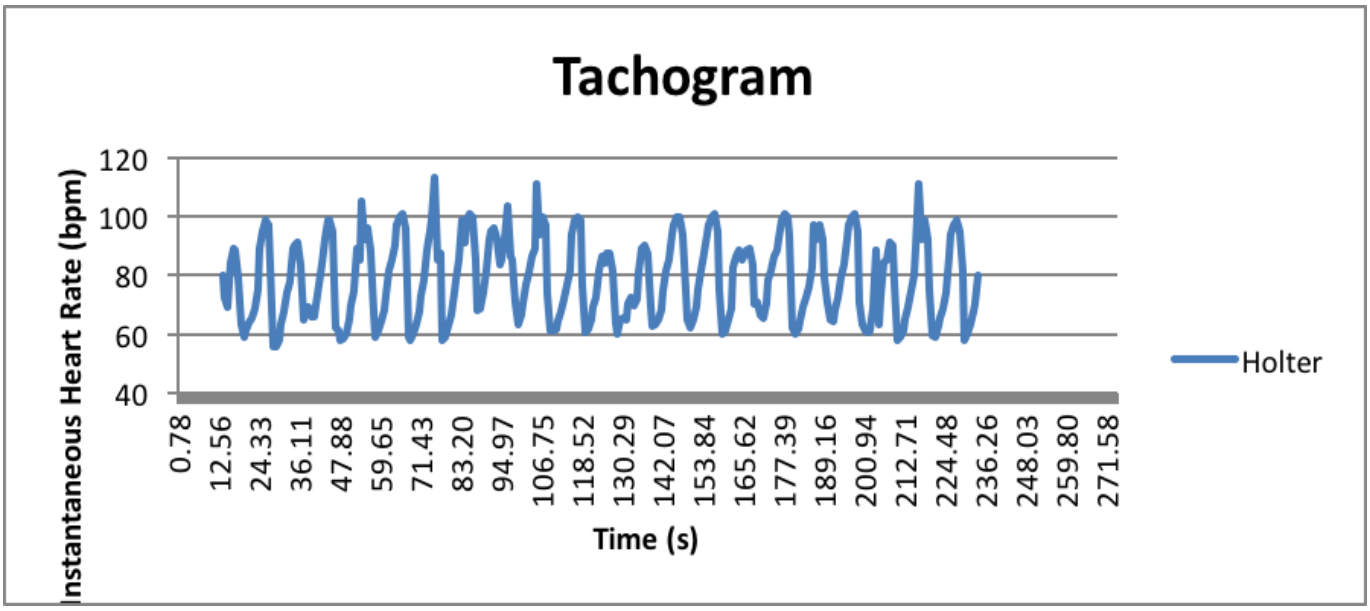


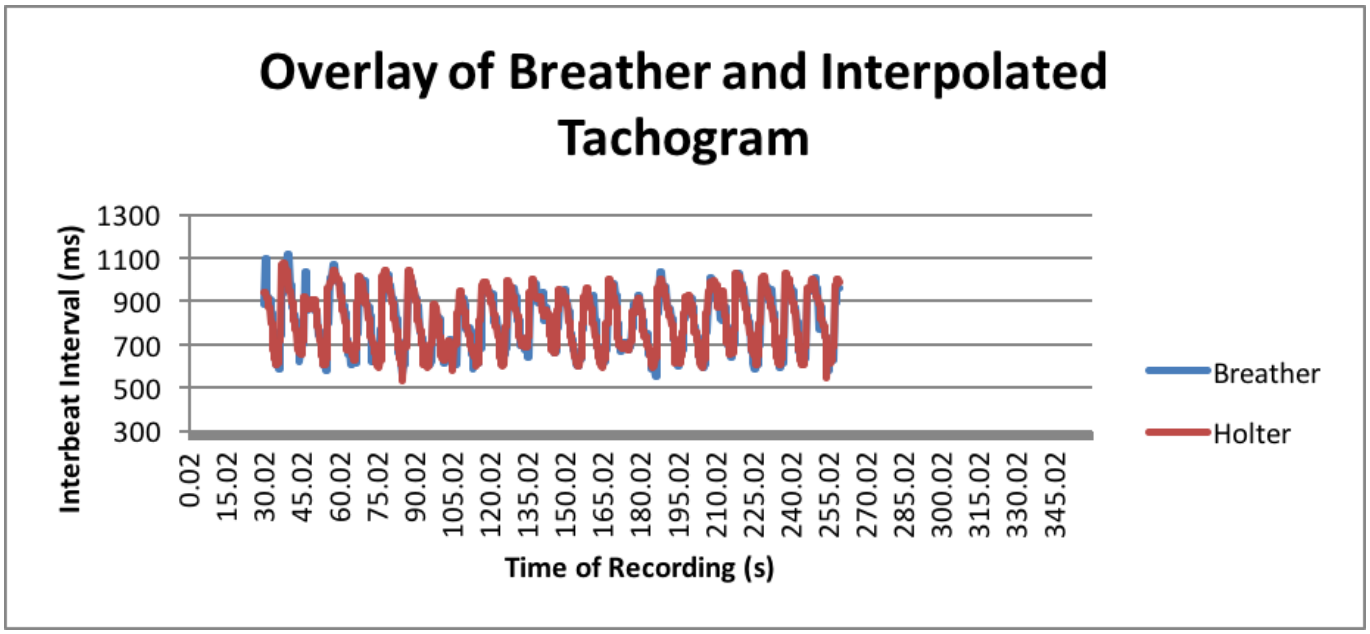
Figure 1. Photograph of a person wearing the myPatch Holter monitor (top) and Breather being used with camera sensor of a mobile phone (bottom)

Breather were e-mailed by the app to the HRV Lab after each breathing trial.

Limitations for Experiment 1. There were some initial difficulties with the Holter hook up, because participants hooked themselves up without sufficient instructions, so that Holter data were not as complete as expected, but usable ECG data obtained at the time of the breather trials were extracted when possible.

After the Holter recordings were scanned on a commercial Holter analyzer (CardioScan, DMS Holter), interbeat intervals were exported and tachograms of instantaneous heart rate, based on accurate detection of the peaks of the R-wave on the ECG (normal heart beats) were plotted. Figure 2 is an example of a segment of the tachogram of instantaneous heart rate from the Holter ECG.





Although the tachograms of instantaneous heart rates are not identical to the continuously varying PPG-based blood flow signals, at the level of the slow-paced breathing used in the app, they should be surrogates for each other. However, because the Holter tachogram and the Breather signal have different sampling rates, and for the sake of direct comparison, the Holter-based tachogram was re-sampled at 50 Hz, using a program written in MATLAB 2016b, so that it was examined at the same sampling rate as the Breather signal. A plot of the Holter-based tachogram signal and the Breather signal was created for each trial separately using the Breather and Holter IBI files for the same period. Figure 3 shows an example of the overlap of the two signals.

Although the Breather signal clearly tracked the respiratory pattern, in some cases there was some visible artifact in the Breather signal, possibly due to finger motion or variations in finger pressure during the Breather exercise. We therefore applied the following filters to the Breather data points:

1. When a visible artifact spike was identified, that value was replaced with the average of the value before and after it.
2. In addition, artifacts were further defined as large spikes in the Breather signal that were physiologically impossible or smaller spikes seen in the middle of an increasing or decreasing heart rate pattern.

Similarly, since there were unusable Holter segments in some cases, due, as stated above, to the initial assumption that the testers would not need assistance in putting their Holters on, only segments with clean Holter signals were used. Clean was defined as lacking spikes in the interbeat interval signal and with maximum and minimum heart rates that were physiologically possible.

Although the Breather exercise takes about 5 minutes, in order to extract the maximum amount of usable Breather data, one-minute periods with simultaneous usable Holter data were compared between devices. As previously stated N=40 simultaneous 1-minute segments were identified.

Furthermore, in an attempt to simplify the identification of clean Breather segments in Experiment 1, the relationship of Breather and Holter segments was further explored by testing a trial selection method. In this experiment, the ability to simplify the identification of usable segments was based on the assumption that significant values for high frequency (HF) HRV spectral power would reflect either excessive noise or non-compliance (i.e., not breathing along with the Breather guide) since the primary HRV spectral power would be expected to be in the low frequency (LF) band during paced breathing. Low HF was defined, for the sake of this experiment, as <58 ms^2 in both the Holter monitor and Breather,

Kubios software (ver 3.1) was used to calculate average, minimum and maximum heart rates, rMSSD (the root mean square of successive differences between normal beats), low frequency power (LF, 0.04-0.015 Hz) and high frequency power (HF, 0.4-0.15 Hz). In addition, because neither LF nor HF power is normally distributed, log LF power and log LF power were computed.

Experiment 2. N=16 simultaneous one-minute trials were obtained in 2 participants who wore a Holter monitor while testing the Breather app. The Breather app had been updated and now included motion detection and finger- present-detection algorithms. These indices were added to the signal file that was emailed by the app. Because of this change, we initially focused on sections where the Breather output indicated that the finger was present and that there was no motion. After taking this into consideration, *i.e.,* excluding segments of the signal where there was evidence for error in the Breather signal acquisition, good segments were chosen just as before. The second change was in the filtering algorithm. Because of better Breather signals**,** filtering was performed in fewer parts of the signals (though performed more aggressively to address spikes). Again, comparisons were made between one-minute periods with simultaneous usable data on both devices.

Limitations in Experiment 2. The thresholds for motion detection and presence of the finger were preset. It would be of interest to customize these thresholds as some individual's hands might be inherently shakier than others, and having an adjustable threshold might improve the specificity of motion detection.

Statistics:

Paired-t-test and correlation analyses were run to compare heart rate and heart rate variability results between the Breather and the Holter signals (2). $P<0.05$ was considered statistically significant. Software was SPSS 24.

Results:

Results are shown in Table 1 below.

Table 1. Results of Experiment 1.

Experiment 1 (N= 40 one minute segments)					
Variable	Breather (mean ± SD)	Holter (mean ± SD)	p-Value of difference	Correlation	p-Value of Correlation
Average HR (bpm)	63.5 ± 8.3	64.6 ± 8.3	0.792	0.952	<0.001
Min HR (bpm)	48.6 ± 7.4	48.4 ± 9.3	0.660	0.931	<0.001
Max HR (bpm)	94.7 ± 11.7	90.3 ± 15.9	0.011	0.761	<0.001
rMSSD (ms)	17.5 ± 3.8	16.0 ± 4.9	0.026	0.600	<0.001
SDNN (ms)	23.1 ± 4.3	20.7 ± 5.5	0.007	0.440	0.004
LF power (ms^2)	281.5 ± 104.5	261.4 ± 146.6	0.412	0.309	0.053
Log LF power	5.6 ± 0.4	5.4 ± 0.6	0.055	0.848	<0.001
Log HF power	5.9 ± 9.9	4.1 ± 0.6	0.267	0.019	0.854
HF power (ms^2)	82.6 ± 31.6	74.0 ± 39.7	0.201	0.338	0.033
Table 1b. Experiment 1 Selected for Low Values for HF (N= 7 one-minute segments)					
Variable	Breather (mean ± SD)	Holter (mean ± SD)	p-Value of difference	Correlation	p-Value of Correlation
Average HR (bpm)	72.7 ± 5.2	73.0 ± 4.9	0.341	0.990	<0.001
Min HR (bpm)	57.6 ± 3.9	60.2 ± 2.3	0.078	0.658	0.108
Max HR (bpm)	99.3 ± 7.6	99.3 ± 13.1	0.996	0.911	0.004
rMSSD (ms)	12.3 ± 1.5	10.5 ± 2.5	0.081	0.523	0.228
SDNN (ms)	17.3 ± 1.9	15.2 ± 3.7	0.101	0.649	0.115
LF power (ms^2)	160.0 ± 33.5	124.4 ± 62.2	0.177	0.417	0.352
Log LF power	5.1 ± 0.2	4.7 ± 0.6	0.107	0.525	0.226
Log HF power	3.8 ± 0.2	3.4 ± 0.5	0.078	0.525	0.226
HF power (ms^2)	46.7 ± 9.4	35.1 ± 17.0	0.121	0.408	0.364

Legend: HR=Heart rate; bpm=beats/minute; Min=minimum; Max=maximum; ms=milliseconds; rMSSD=root mean square of successive differences of interbeat intervals, equivalent to the absolute value of the average change in interbeat interval from one beat to the next; SDNN=standard deviation of interbeat intervals for the entire period of interest; LF power= low frequency power which reflects the amount of variation in heart rate accounted for by changes in the range of 3 to 9 cycles/minute; Log=logarithm; HF=High frequency power, the amount of variation in heart rate at 9-24 cycles/minut.During spontaneous breathing HF power is generally due to respiratory sinus arrhythmia

Table 2. Results of Experiment 2.

Experiment 2 (N= 16 one-minute segments)					
Variable	Breather (mean ± SD)	Holter (mean ± SD)	p-Value of difference	Correlation	p-Value of Correlation
Average HR (bpm)	64.0 ± 8.0	64.0 ± 7.5	0.939	0.936	<0.001
Min HR (bpm)	48.3 ± 6.7	47.9 ± 6.9	0.377	0.967	<0.001
Max HR (bpm)	92.1 ± 7.3	91.7 ± 12.3	0.902	0.554	0.026
rMSSD (ms)	17.1 ± 4.4	17.1 ± 5.0	0.483	0.821	<0.001
SDNN (ms)	22.5 ± 5.1	22.7 ± 5.6	0.808	0.777	<0.001
LF power (ms^2)	281.4 ± 117.1	301.0 ± 152.4	0.508	0.656	0.006
Log LF power	5.6 ± 0.5	5.6 ± 0.5	0.521	0.781	0.001
Log HF power	4.3 ± 0.4	4.3 ± 0.46	0.028	0.769	0.001
HF power (ms^2)	79.3 ± 32.1	84.4 ± 42.0	0.568	0.645	0.007

Legend: See legend for Table 1.

Discussion

Overall results clearly show the ability of the iPhone-based Breather app to capture heart rate changes associated with performing paced breathing. As can be seen from the Tables, the correlations of average heart rate between the devices was nearly perfect with no significant differences between devices. One of the testers was dark-skinned and the Breather worked just as well for him, suggesting the generalizability of this technology is not dependent on light skin color.

Examination of comparisons for rMSSD, a sensitive measure of beat to beat changes in magnitude of intervals between heart rates also shows that the two methods produce equivalent results. This HRV parameter is highly sensitive to noise and it is encouraging that in Experiment 2, with better signals on both devices, rMSSD was not significantly different between devices and correlations were better than 0.82. Continuing down the variable list, SDNN is a measure of the total HRV during each segment. Once again, although SDNN performed reasonably well in experiment 1, it is notable that in experiment 2, SDNN was not different between devices and the correlation was 0.78.

When LF power (or more specifically log LF power because of the non-normal distribution of the data), the primary HRV marker for the paced breathing effect on HRV was compared between devices, differences were not significant for any of the experiments or sub experiments. LF power would be the least affected by small noise spikes and correlations between devices were excellent and highly statistically significant.

Conclusions

Our results support the feasibility of using the iPhone Breather app to accurately track heart rate changes during the Breather exercise. Results obtained on the Breather were consistent with those obtained using the Holter recorder.

References

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