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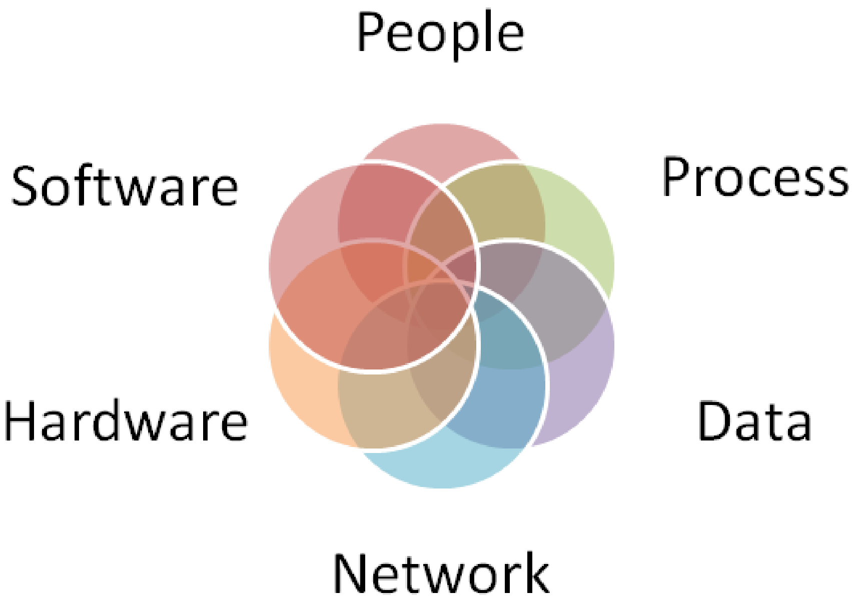

Vol. 10 No. 01 Desember 2021

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jurnal sisfo
Jurnal Sisfo Vol. 10 No. 01 (2021) i–ii

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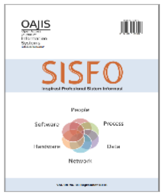

Assessing heart condition using a consumer-grade wearable PPG wristband: A preliminary study

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Abstract

The heart is one of the critical parts of humans. It regulates blood circulation, in which the blood carries oxygen and nutrients to all body parts, carries the metabolic waste such as carbon dioxide back to the heart, and delivers it to the lungs to release it during respiration. Since the heart's function is essential, it is needed to be able to check the heart condition periodically. The conventional way to check heart condition is by going to a hospital or clinic to perform a clinical health checkup. However, it costs high and sometimes takes time to get the result; thus, an efficient and effective way needs to be investigated. Recently, consumer-grade wristband heart sensors have been significantly produced. It uses an infrared sensor to assess the Photoplethysmogram (PPG). Using this method enables people to assess the heart activity by only placing the wristband on the arm instead of placing some electrodes on the chest by assessing the electroencephalogram (ECG). This study aims to investigate the possibility of assessing heart condition using a consumer-grade heart wristband sensor (Polar OH1). Ten men participated in this study. They were instructed to wear the heart wristband sensor on their right arm, then perform a resting-state condition by sitting on a chair, do exercise by running around, and assess the heart condition after the exercise. Each subject performed each activity in 10 minutes. In this study, we also used a conventional heart sensor placed on the participants' chest during the recording of the wristband sensor. There are 14 parameters (MeanRR, SDRR, CVRR, SDSD, RMSSD, NN50, pNN50, VLF, LF, HF, TP, LFHF, LFnorm, and HFnorm) where extracted from both PPG and ECG data by using time and frequency-domain analysis. As a result, by using the PPG data obtained from the wristband sensor, six parameters have a statistically significant decrement ($p < 0.05$) in comparison to pre and post-exercise conditions. In addition, the PPG analysis was also showed a similar or even superior result compared to the ECG analysis. Therefore, a consumer-grade wristband heart sensor can be used as an effective and efficient way to assess heart conditions.

Keywords: heart condition, photoplethysmogram, PPG, wearable sensor

Article history: Submitted 16 Dec 2020 ; Revised 14 Dec 2021; Accepted 26 Dec 2021; Available Online 26 Dec 2021

1. Introduction

The heart is an organ that regulates blood circulation. It pumps the blood containing oxygen and nutrients to all body parts through the blood vessel. After the oxygen and nutrients are delivered to all body parts, it will carry the metabolic waste from all body parts to the heart. The metabolic waste such as carbon dioxide will

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https://doi.org/10.24089/j.sisfo.2020.09.003 (DOI)

be delivered to the lungs to secrete during respiration [1]. It produces a small electrical activity during the heart activity, starting when the blood enters the heart from the left atrial to the blood pumps out from the heart by the right ventricle area [2]. This small electrical activity can be assessed by placing some electrodes on the chest or limbs by following some rules of electrode placement. This small electrical activity is called the electrocardiogram (ECG) [3]. ECG is widely used for assessing heart conditions during many activities [4]–[7]. However, since it usually costs high and needs some expertise to assess the signal, it is usually used in the hospital or clinic.

Recently, many companies produced many wearable heart sensors to solve the problem. It utilizes photoplethysmography to assess the Photoplethysmogram (PPG). Photoplethysmography detects the skin blood flow using an infrared sensor [8]. Unlike the ECG, the PPG sensor or Photoplethysmography does not need many electrodes. It only uses an infrared sensor placed on the human body part, usually in the fingertip [9], [10]. The sensor illuminates the light to the skin and the sensor will detect the changes in the blood flow volume through the reflection of the light on the skin. Since it does not need many electrodes to be placed, it is convenient to be used by the regular user who does not have expertise in the medical or clinical field. Even though it has advantages compared to the ECG, however, the ability of the PPG sensor, moreover a consumer-grade PPG sensor, to be used for assessing heart condition needs to be investigated.

Therefore, the purpose of this study is to investigate the possibility of the consumer-grade wearable PPG sensor to be used for assessing heart conditions. This study is also trying to investigate the comparison of PPG and ECG in assessing heart condition. As the preliminary study, this study is trying to analyze the condition of resting-state and post-exercise since this task is widely used in heart condition analysis.

2. Previous studies

Electrocardiogram (ECG) becomes the standard evaluation of heart health conditions. Marinho et al. [4] used ECG to detect cardiac arrhythmia by using Structural Co-Occurrence Matrix (SCM) to extract the parameters. They claimed that using the standard classification method (Support Vector Machine, Multi-Layer Perceptron, Bayesian, and Optimum-Path Forest), they could detect cardiac arrhythmia up to 2% higher than the previous studies.

Finocchiaro et al. [7] used ECG to detect hypertrophic cardiomyopathy (HCM). They analyzed the morphology of the ECG signal and determined the disease from the ECG wave occurrences. They stated that the Nonsustained Ventricular Tachycardia (NSVT) has a relationship with the patient of HCM. They observe the occurrences of 3 or more consecutive beats at a rate of more than 100 beats/min with a duration of fewer than 30 seconds. On the other hand, HCM was also able to detect from the ST-T segment of ECG, which decreased in patients with HCM. In conclusion, they stated that ECG could detect the HCM disease.

Electrocardiograms are also used for detecting sleep apnea disease [5]. They extracted the parameters from the combination of deep learning methods: Deep Neural Network (DNN), one-dimensional (1D) Convolutional Neural Networks (CNN), two-dimensional (2D) CNN, Recurrent Neural Networks (RNN), Long Short-Term Memory, and Gated-Recurrent Unit (GRU). They concluded that the designed deep learning approaches performed better than those developed and tested in previous studies.

ECG was also widely used in human psychological condition research. Scherz et al. [11] tried to investigate the possibility of ECG signals as a parameter to detect stress on people. They measured the RR interval of ECG and the Root Mean Square of the Successive Differences (RMSSD). As a result, they can detect the stress condition using the parameter.

Zhuonan et al. [12] also tried to investigate the possibility of the ECG as a parameter to detect stress conditions. They used the social media approach, in which they hypothesized that the abnormal heart rates were caused by stressors coming from the linguistic posts on microblogs. In conclusion, they stated that the SDNN (Standard Deviation of NN-interval) is the most appropriate indicator of stress condition.

Another study used ECG to detect three human emotion conditions (neutral, fear, and disgust) [13]. The study extracted the ECG into several parameters by using time-domain analysis. This study implemented two machine learning techniques, Logistic Regression and Artificial Neural Network, to compare. The result of this study is that the ECG parameter can be used for distinguishing the three specific emotions (neutral, fear, and disgust) across multiple subjects (25 subjects).

Even though it is not directly assessed the heart activity, Photoplethysmogram (PPG) shows a promising method to assess heart condition. Huang et al. [10] used the PPG to assess Blood Pressure (BP). They used a weighted pulse decomposition technique, and as a result, they stated that the PPG could be used for enhanced Blood Pressure assessment. Banerjee et al. [14] tried to use PPG as a parameter to detect Coronary Artery Disease (CAD). They used machine learning (SVM) to distinguish CAD and non-CAD subjects. As a result, they claimed that they could achieve the sensitivity up to 0.82 and specificity up to 0.88.

Even though it showed a promising result from several studies, all previous studies used a clinical fingertip PPG sensor instead of a wristband-type PPG sensor. Thus, it still needs to investigate whether the consumer-grade PPG sensor can be used as a tool to assess the heart condition.

3. Methodology

The methodology of this study consists of subjects, experiment procedures, recordings, feature extraction, and statistical analysis.

3.1 Subjects

Ten men participated in this study in the age group 18-64 years old (Age: 32.8 ± 17.8 years old). On the day before the experiment, they were instructed to rest at least 10 hours during sleep at night, refrain from any caffeine beverages, smoking, fasting, and medical prescription. They are asked to have breakfast in the morning before the experiment. On the day of the experiment, they interviewed for their health condition. If the subject is not healthy or meets the condition described above, the experiment has to be rescheduled.

3.2 Experiment procedures

Each subject conducted all of the experiments in two days. Each day they only have one trial, starting from 10:00 to 10:30. In total, each subject performs two trials. There are three stages in each experiment: pre-exercise resting, running, and post-exercise resting, as shown in Figure 1. In the first stage, the subject was instructed to perform a resting state by sitting down on a chair for 10 minutes. The second stage is the subject asked to run around for 10 minutes. The last stage is the subject instructed to sit down, similar to the first stage. The subject only examined the PPG and ECG in the first and third stages. During PPG and ECG examination, they were instructed to maintain their resting state without body movements. The subjects were prohibited from having a meal and beverages during the experiment. If there is a problem during the recording or the subject feels unhealthy in the middle of the experiment, the experiment will be rescheduled on a different day.

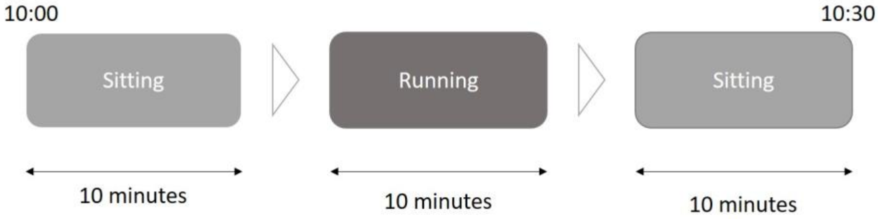


Figure 1. Experiment schedule of each experiment

3.3 Recordings

ECG signals were recorded using portable electrocardiography (Heal Force Prince 180D, Heal Force, China) with four electrodes. This study used the standard Limb Lead 2 as the electrode placement of ECG, as shown in Figure 2 (a). The electrocardiography has a 150Hz sampling frequency and has a disposable electrode cap for each electrode with the electrolyte to get an excellent impedance to the skin.

(a)

(b)

Figure 2. (a) Electrode placement used in this study; (b) The placement of the PPG sensor

On the other hand, PPG signals were recorded by a wearable wristband heart sensor (Polar OH1, Polar, Finland) with an infrared sensor on the bottom side of the wristband. The subjects wear the PPG sensor on their right arm, as shown in Figure 2 (b) The PPG sensor or photoplethysmography has a 130Hz sampling frequency. The sensor has to connect to a smartphone by an application to record the PPG signal through a Bluetooth connection. The PPG data will be saved in the smartphone memory and moved to the PC for analysis.

3.4 Feature extraction

ECG and PPG signals were preprocessed to remove the body movement artifacts on the signals by subtracting the lowpass filter (Butterworth filter with order = 5) from the original signal. After obtaining a clean signal, since both signals have a different sampling frequency, the PPG signals were resampling into 150Hz.

The next step is detecting the peaks of both signals and the interval between peaks was calculated. The interval peak will be used as input to several parameters. The parameters used in this study are extracted from time-domain and frequency-domain analysis. The parameter extracted by time-domain analysis are:

$$MeanNN = \frac{1}{N}\sum_{i=1}^{n} NN_i \quad (1)$$

$$SDNN = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(NN_i - MeanNN)^2} \quad (2)$$

$$CVNN = \frac{SDNN}{MeanNN} \times 100 \quad (3)$$

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

$$SDSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(|NN_i - NN_{i+1}| - \overline{NNd\imath f})^2} \quad (5)$$

$$\overline{NNd\imath f} = \frac{1}{N-1}\sum_{i=1}^{N-1}(|NN_i - NN_{i+1}|) \quad (6)$$

Which NN_i means the interval between peaks in the signals, and N is the number of NN intervals. The other parameters are NN50, the number of NN intervals that have a value more than 50 ms, and pNN50, which is the percentage of NN50.

The NN intervals will be calculated by using the fast Fourier Transform (FFT) to extract four common frequency bands. They are VLF (Very Low Frequency), LF (Low Frequency), HF (High Frequency), and TP (Total Power) which has frequency range 0.0033-0.04 Hz, 0.04-0.15 Hz, 0.15-0.4 Hz and 0.0033-0.4 Hz, respectively. The other parameters are:

$$LFHF = \frac{LF}{HF} \quad (7)$$

$$LFnorm = \frac{LF}{LF+HF} \times 100 \quad (8)$$

$$HFnorm = \frac{HF}{LF+HF} \times 100 \quad (9)$$

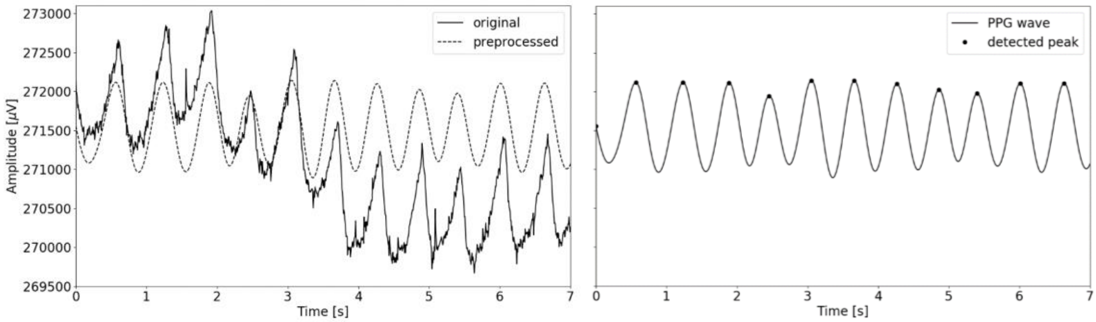
In total, there are 14 parameters extracted from both time and frequency domain analysis.

3.5 Statistical analysis

We investigated the difference between the pre and post-exercise heart conditions. Kolmogorov-Smirnov test was used to examine whether the data distribution followed by normal distribution or not. A one-way ANOVA analysis will be used if a normal distribution follows the data distribution, or the Kruskal-Wallis test will be used if a normal distribution does not follow the data distribution. A value of $p<0.05$ was considered statistically significant.

4. Results and Discussion

First, the data needs to be cleaned by preprocessing the data. The result of the preprocessing stage is shown in Figure 3 (a) below. Even though the subject has been instructed to maintain their resting state condition and prohibited doing any body movements, they still did some body movements. When we interviewed the subject, they stated that they could not stop moving their bodies sometimes. Thus, the body movements were non-voluntary movements. To accommodate this movement, we implemented the preprocessing method to all subjects' data in every trial. As shown in Figure 3 (a) below, the result of the preprocessing method showed a relatively stable wave compared to the original signal. In the original signal that did not contain body movement, for example, at the 2-3 seconds period, the preprocessed result was similar to the original wave with a cleaner wave shape.



(a) (b)

Figure 3. (a) Preprocessing result; (b) Detecting peaks of the signal

After obtaining the clean data, the peak of the signal is calculated. The result of detecting the peaks of the signal is shown in Figure 3 (b) above. As shown in Figure 3 (b), the peaks were detected successfully by using the cleaned data from the previous step. The interval between detected peaks was then computed, and the result of the interval is called the NN interval. The NN interval was used to extract the 14 parameters. After obtaining the 14 parameters, a statistical test for the pre and post-exercise heart data needs to be conducted. The result of the statistical analysis between pre and post-exercise conditions of PPG data are shown in Table 1-5 below.

Table 1. Result of statistical analysis for MeanNN, SDNN, and CVNN of PPG data

	MeanNN		**SDNN**		**CVNN**	
	Pre	Post	Pre	Post	Pre	Post
S1	94.16±1.2	75.24±1.6***	3.75±1.28	1.29±0.4***	15.88±12.09	1.85±1.15***
S2	93.21±3.97	75.43±1.78***	7.67±0.96	2.9±0.98***	60.43±15.4	9.44±6.97***
S3	109.96±2.69	80.98±3.96***	7.49±1.46	2.38±0.9***	59.0±22.3	6.52±5.0***
S4	106.07±1.97	73.11±2.82***	5.98±1.08	5.61±3.03	37.36±13.57	40.96±40.77
S5	89.72±1.92	82.2±1.65***	9.46±1.09	11.16±2.79	91.6±20.28	133.63±58.37
S6	112.55±2.87	109.33±2.88*	9.86±2.93	9.75±2.01	107.1±61.54	100.37±46.63
S7	91.26±0.97	75.3±1.9***	4.47±0.89	2.25±1.04***	20.97±8.37	6.18±6.95***
S8	123.04±2.0	121.47±2.02	4.75±1.65	4.55±2.02	25.67±19.03	25.13±27.85
S9	108.6±2.66	97.35±4.0***	6.33±2.02	5.19±1.5	44.72±30.0	29.5±15.09
S10	110.48±2.25	100.21±5.76***	13.82±4.9	14.25±5.37	217.7±133.71	234.6±143.6

Table 2. Result of statistical analysis for RMSSD, SDSD, and NN50 of PPG data

	RMSSD		**SDSD**		**NN50**	
	Pre	Post	Pre	Post	Pre	Post
S1	94.24±1.22	75.25±1.6***	3.11±1.29	1.3±0.37***	94.4±1.43	0.0±0.0***
S2	93.53±4.0	75.49±1.76***	6.85±1.07	1.91±1.42***	87.1±6.11	2.6±4.03***
S3	110.23±2.62	81.02±3.95***	5.91±0.83	1.92±0.93***	81.0±1.95	43.9±31.18***
S4	106.24±1.99	73.39±2.8***	5.07±1.57	7.07±3.85	83.6±1.69	2.9±2.74***
S5	90.23±1.93	83.0±1.91***	13.99±1.72	16.57±4.05	78.9±4.66	45.7±6.72***
S6	113.02±2.71	109.78±2.87*	8.4±3.79	9.16±2.24	77.9±1.37	79.8±2.04*
S7	91.38±0.99	75.34±1.91***	3.3±0.53	2.33±2.24***	95.0±1.9	0.6±1.28***

S8	123.15±2.01	121.57±2.06	3.92±1.83	4.24±2.77	72.1±1.04	73.0±1.34
S9	108.81±2.55	97.5±4.03***	6.03±2.61	4.39±2.03	81.3±1.55	90.7±3.63***
S10	111.45±1.97	101.4±5.11***	14.93±5.03	18.73±6.22	75.6±2.76	75.6±8.3

Table 3. Result of statistical analysis for pNN50, VLF, and LF of PPG data

	pNN50		**VLF [x10^5]**		**LF [x10^5]**	
	Pre	Post	Pre	Post	Pre	Post
S1	99.79±0.42	0.0±0.0***	15±0.10	13±0.25***	15±0.10	13±0.25***
S2	91.35±9.19	2.25±3.51***	15±0.39	13±0.27***	15±0.39	13±0.27***
S3	100.0±0.0	41.13±29.72***	17±0.30	14±0.52***	17±0.30	14±0.52***
S4	99.64±0.77	2.38±2.22***	17±0.29	13±1.11***	17±0.28	13±1.11***
S5	79.57±6.06	42.26±6.98***	15±0.21	14±0.28***	15±0.21	14±0.28***
S6	98.63±1.78	98.04±1.49	17±0.30	17±0.27	17±0.29	17±0.27
S7	97.35±2.14	0.52±1.12***	15±0.99	13±0.28***	15±0.10	13±0.28***
S8	99.86±0.42	99.86±0.42	18±0.29	18±0.26	18±0.29	18±0.26
S9	99.29±1.5	99.02±1.15	17±0.19	16±0.41***	17±0.19	16±0.41***
S10	93.98±4.46	85.69±13.78	17±0.27	16±0.39***	17±0.27	16±0.39

Table 4. Result of statistical analysis for HF, TP, and LFHF of PPG data

	HF [x10^5]		**TP [x10^5]**		**LFHF**	
	Pre	Post	Pre	Post	Pre	Post
S1	15±0.10	13±0.25***	15±0.10	13±0.25***	1.0±0.0	1.0±0.0
S2	15±0.39	13±0.27***	15±0.39	13±0.26***	1.0±0.0	1.0±0.0
S3	17±0.29	14±0.52***	17±0.30	14±0.51***	1.0±0.0	1.0±0.0
S4	17±0.28	13±1.11***	17±0.28	13±1.11***	1.0±0.0	1.0±0.0
S5	15±0.21	14±0.28***	15±0.21	14±0.28***	1.0±0.0	1.0±0.0
S6	17±0.29	17±0.27	17±0.29	17±0.26	1.0±0.0	1.0±0.0
S7	15±0.99	13±0.28***	15±0.99	13±0.28***	1.0±0.0	1.0±0.0
S8	18±0.29	18±0.26	18±0.29	18±0.26	1.0±0.0	1.0±0.0
S9	17±0.19	16±0.41***	17±0.19	16±0.40***	1.0±0.0	1.0±0.0
S10	17±0.27	16±0.39	17±0.27	16±0.39	1.0±0.0	1.0±0.0

Table 5. Result of statistical analysis for LFnorm and HFnorm of PPG data

	LFnorm		**HFnorm**	
	Pre	Post	Pre	Post
S1	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S2	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S3	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S4	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S5	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S6	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S7	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S8	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S9	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S10	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0

By considering the result of the statistical analysis in Table 1-5 above, MeanNN showed a decrement tendency in all of the subjects, with 9 out of 10 subjects having a statistically significant difference between pre and post-exercise conditions. SDNN showed that five subjects have a decrement tendency, two subjects have an increment tendency, and three subjects have no-tendency. Four subjects who had a statistically significant difference showed a decrement tendency. CVNN showed that six subjects have a decrement tendency, two subjects have an increment tendency, and two subjects have no-tendency. Four subjects significantly differ between pre and post-exercise conditions with a decrement tendency. RMSSD showed a decrement tendency for all subjects, with 9 out of 10 statistically significant differences. SDSD showed that five subjects have a decrement tendency, and the other five subjects have an increment tendency. Four of five subjects with a decrement tendency showed a statistically significant difference.

NN50 showed that six subjects have a decrement tendency, three subjects have an increment tendency, and one subject has no-tendency. All six subjects with a decrement tendency showed a statistically significant difference. pNN50 showed that seven subjects have a decrement tendency, and three subjects have an increment tendency. Six of seven subjects with a decrement tendency showed a statistically significant difference. VLF, LF, HF, and TP showed a similar result of the statistical analysis. The four parameters showed that eight subjects had a statistically significant decrease tendency. In addition, LFHF, LFnorm, and HFnorm showed a similar result that all of the subjects have a no-tendency and no statistically significant difference observed. The statistical analysis results between pre and post-exercise conditions of ECG data are shown in Table 6-10 below.

Table 6. Result of statistical analysis for MeanNN, SDNN, and CVNN of ECG data

	MeanNN		**SDNN**		**CVNN**	
	Pre	Post	Pre	Post	Pre	Post
S1	104.48±1.05	83.38±1.78***	8.93±0.92	3.27±1.83***	81.52±16.8	14.2±20.27***
S2	104.08±3.79	84.13±2.12***	9.26±1.3	5.12±1.97***	88.54±24.86	30.34±26.23***
S3	112.03±4.69	89.19±4.18***	26.6±3.3	2.91±1.23***	727.8±173.96	10.09±9.38***
S4	117.69±2.04	82.14±4.64***	6.42±0.85	10.16±6.08	42.47±10.58	141.61±134.95
S5	99.92±1.87	90.49±1.51***	3.91±0.97	3.35±0.62	16.41±8.21	11.72±4.36
S6	125.82±3.89	119.77±2.54***	9.21±3.43	13.35±5.61	98.05±82.8	212.44±175.99
S7	101.22±1.34	83.47±1.86***	5.84±1.25	9.31±1.61***	36.03±16.31	90.02±31.01***
S8	126.95±6.15	129.12±4.58	21.57±10.4	18.28±5.83	581.21±413.54	373.56±230.96
S9	89.47±7.91	97.24±3.46*	27.4±1.31	20.41±3.73***	760.35±71.29	435.13±165.24***
S10	67.46±0.77	110.21±4.14***	16.57±2.53	28.76±2.93***	282.97±83.5	846.19±173.36***

Table 7. Result of statistical analysis for RMSSD, SDSD, and NN50 of ECG data

	RMSSD		**SDSD**		**NN50**	
	Pre	Post	Pre	Post	Pre	Post
S1	104.87±1.07	83.47±1.83***	14.49±1.74	4.86±2.82***	84.4±1.28	66.0±23.03*
S2	104.5±3.86	84.31±2.15***	9.97±1.66	6.56±3.41*	84.9±3.45	63.7±16.65*
S3	115.21±4.26	89.25±4.18***	36.14±4.49	2.95±1.2***	64.2±4.77	88.0±22.83***
S4	117.87±2.05	82.96±5.17***	5.31±0.63	13.03±7.23*	75.5±1.2	40.2±22.36***
S5	100.01±1.89	90.55±1.5***	3.34±0.38	4.0±1.19	89.1±1.64	96.8±2.44***
S6	126.21±3.82	120.65±2.26***	7.76±3.84	13.72±7.67	70.2±2.14	71.9±2.55
S7	101.39±1.32	84.0±1.88***	6.22±1.2	13.35±2.25***	87.2±0.75	54.6±10.19***
S8	129.25±4.61	130.56±3.89	26.48±11.71	20.62±6.57	65.2±1.17	65.9±1.3
S9	93.62±7.44	99.45±2.72	34.03±2.76	26.79±3.7***	47.1±11.49	68.0±8.79***
S10	69.51±1.14	113.96±3.47***	23.27±2.94	43.84±2.99***	7.8±2.68	57.0±4.0***

Table 8. Result of statistical analysis for pNN50, VLF, and LF of ECG data

	pNN50		**VLF [x10^5]**		**LF [x10^5]**	
	Pre	Post	Pre	Post	Pre	Post
S1	99.06±0.88	62.17±22.24***	16±0.90	14±0.22***	16±0.89	14±0.22***
S2	99.17±1.19	60.5±17.12***	16±0.38	14±0.28***	16±0.38	14±0.28***
S3	81.12±8.12	89.09±24.41*	18±0.45	15±0.44***	18±0.45	15±0.44***
S4	100.0±0.0	38.17±21.65***	18±0.31	14±0.80***	18±0.31	14±0.80***
S5	100.0±0.0	98.32±3.26*	16±0.23	15±0.15***	16±0.23	15±0.15***
S6	99.45±1.64	96.93±3.77*	19±0.38	18±0.27***	18±0.38	18±0.27***
S7	99.22±1.0	51.26±10.18***	16±0.14	14±0.23***	16±0.14	15±0.23***
S8	93.17±5.67	95.87±2.98	19±0.47	19±0.43	19±0.47	19±0.43
S9	48.4±15.53	74.73±11.85***	16±0.60	16±0.17	16±0.64	16±0.17
S10	5.91±2.07	70.86±6.88***	11±0.90	18±0.28***	11±0.90	18±0.28***

Table 9. Result of statistical analysis for HF, TP, and LFHF of ECG data

	HF [x10^5]		**TP [x10^5]**		**LFHF**	
	Pre	Post	Pre	Post	Pre	Post
S1	16±0.89	14±0.22***	16±0.89	14±0.22***	1.0±0.0	1.0±0.0
S2	16±0.38	14±0.28***	16±0.38	14±0.28***	1.0±0.0	1.0±0.0
S3	18±0.45	15±0.44***	18±0.45	15±0.44***	1.0±0.0	1.0±0.0
S4	18±0.31	14±0.80***	18±0.31	14±0.80***	1.0±0.0	1.0±0.0
S5	16±0.23	15±0.15***	16±0.23	15±0.15***	1.0±0.0	1.0±0.0
S6	18±0.38	18±0.27***	18±0.38	18±0.27***	1.0±0.0	1.0±0.0
S7	16±0.14	15±0.23***	16±0.14	15±0.23***	1.0±0.0	1.0±0.0
S8	19±0.47	19±0.41	19±0.47	19±0.43	1.0±0.0	1.0±0.0
S9	16±0.64	16±0.17	16±0.64	16±0.17	1.0±0.0	1.0±0.0
S10	11±0.90	18±0.28***	11±0.90	18±0.28***	1.0±0.0	1.0±0.0

Table 10. Result of statistical analysis for LFnorm and HFnorm of ECG data

	LFnorm		**HFnorm**	
	Pre	Post	Pre	Post
S1	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S2	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S3	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S4	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S5	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S6	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S7	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S8	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S9	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0
S10	50.0±0.0	50.0±0.0	50.0±0.0	50.0±0.0

By considering the result of the statistical analysis in Table 6-10 above, MeanNN showed a decrement tendency in seven subjects, with all of the subjects having a statistically significant difference and an increment tendency in four subjects. SDNN showed that five subjects have a decrement tendency, four subjects have an increment tendency, and one subject has no-tendency. Four of five subjects who showed a decrement tendency have a statistically significant difference. CVNN showed that six subjects have a decrement tendency, and four have an increment tendency. Four subjects significantly differ between pre and post-exercise conditions with a decrement tendency. RMSSD showed a decrement tendency for all subjects, with 9 out of 10 statistically significant differences. SDSD showed that five subjects have a decrement tendency, and the other five subjects have an increment tendency. Four of five subjects with a decrement tendency showed a statistically significant difference.

NN50 showed that six subjects have a decrement tendency, three subjects have an increment tendency, and one subject has no-tendency. All six subjects with a decrement tendency showed a statistically significant difference. pNN50 showed that seven subjects have a decrement tendency, and three subjects have an increment tendency. Six of seven subjects with a decrement tendency showed a statistically significant difference. VLF, LF, HF, and TP showed a similar result of the statistical analysis. The four parameters showed that eight subjects had a statistically significant decrease tendency. In addition, LFHF, LFnorm, and HFnorm showed a similar result that all of the subjects have a no-tendency and no statistically significant difference observed.

This experiment used a simple approach to assess the ability of a customer-grade wearable wristband by using an exercise to stimulate heart activity. During exercise, the heart increases blood circulation by pumping the blood faster. When the blood pumps faster, the more oxygenated blood arrives in the muscle to move the body [2]. This activity causes a reduction the heart rate variability during exercise. Almost all of the parameters showed a decrement tendency between pre and post-exercise conditions in this study. Previous studies also showed that heart rate variability during exercise decreases [15]. Our study's interesting findings are that subject #8 constantly had no significant difference and had an opposite tendency to majority subjects in all of the parameters. We interviewed the subjects that we found the subject diagnosed as the coronary disease patient after several months of the experiment. It means the parameters can be used as the early detection of abnormal heart activity. Even though we found that the opposite tendency or the increasing of heart rate variability during exercise is a sign of heart disease in this study, another study stated that the increment of the heart rate variability during exercise is not associated with heart disease [16]. Thus, further investigation with more subjects is needed to investigate the association of the increment of the heart rate variability with heart disease.

Even though the ECG is well-known as the best parameter to assess heart conditions [4]–[7], the pre- and post-exercise condition seems inferior to PPG. According to this study result, some parameters in the PPG data showed that the number of subjects with a statistically significant difference is higher than in the ECG data. Moreover, those subjects also showed a similar tendency among each other. This inferior result of ECG might be caused by the sweat secreted in the post-exercise condition that can affect the ability of the ECG sensor placed in the subject's chest even though we have cleaned the sweat before placing the electrode to the chest.

5. Conclusion

Heart disease is one disease that contributes to many deaths in various countries. Many studies have been conducted to address this issue, including the possibility of detecting heart activity with wearable sensors. Wearable sensors can provide real-time heart information by utilizing a small sensor that is easy to use and suitable for daily life. Even some wearable sensor manufacturers add many features such as clocks to be worn like a watch. This research tried to investigate whether the consumer-grade PPG sensor can be used as a tool to assess heart conditions. This study used subjects with the age range most frequently experiencing heart disease to obtain valid results. According to the result, the customer-grade wearable PPG wristband can assess the heart condition during pre and post-exercise using time and frequency-domain analysis. We suggested using six parameters: MeanNN, RMSSD, VLF, LF, HF, and TP in PPG to obtain a good result. We conclude that the heart condition can be assessed using a consumer-grade wristband PPG sensor, and the device has a similar ability as a conventional ECG sensor.

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