SAKARYA UNIVERSITY JOURNAL OF COMPUTER AND INFORMATION SCIENCES
VOL. 5, NO. 1, APRIL 2022
DOI: 10.35377/saucis.05.01. 1024414

*Research Article*

# Detection of Heart Rate Variability from Photoplethysmography (PPG) Signals Obtained by Raspberry Pi Microcomputer

Ziynet Pamuk[1], Ceren Kaya[2]
[1]Corresponding Author; Zonguldak Bulent Ecevit University, Department of Biomedical Engineering, Zonguldak, Turkey; ziynet.pamuk@beun.edu.tr; +90 372 291 26 23
[2] Zonguldak Bulent Ecevit University, Department of Biomedical Engineering, Zonguldak, Turkey; ceren.kaya@beun.edu.tr, crnkaya@hotmail.com;

Received 16 November 2021; Revised 30 March 2022; Accepted 26 April 2022; Published online 30 April 2022

## Abstract

Photoplethysmography (PPG) signals are signals obtained as a result of optically measuring volumetric changes in capillaries. Volumetric changes in capillaries also depend on the work of heart. According to recent researches, it has been seen that PPG signals contain a lot of information about the physiological and biological state of related person. Most of these studies are based on the analysis of characteristics and waveforms of PPG signals obtained with a single wavelength in time and frequency domains. In this study, 10 minutes of data was taken from the left index finger of a 24-year-old male, which was positioned horizontally using a MAX30100 sensor and Raspberry Pi 4 microcomputer. Experiments are carried out in the fully resting state of a male volunteer in outdoors and stressful environments. While the MAX30100 sensor shows the heartbeat on the screen, it also gives PPG signal data, which is a single wavelength, into a .csv file as received data. In these cases, five different time domain parameters of received PPG signals are extracted. When the results are interpreted, it is seen that all results are meaningful and consistent.

**Keywords:** photoplethysmography, heart rate variability, time domain parameters, raspberry pi

## 1. Introduction

Heart rate variability (HRV), which is a non-invasive measurement, is an important parameter in the prognosis of some diseases, especially cardiovascular diseases. The parameter called HRV, which is revealed by making use of the effect of the sympathetic branch of the autonomic nervous system (ANS) accelerating heart and parasympathetic branch (nervus vagus) slowing the heart, is also used as an important stress measurement parameter in terms of providing information about the sympathovagal balance. Changes in ANS activation are different in patients and healthy individuals.

ANS responds to internal and external factors by regulating visceral functions such as cardiovascular function, respiration, thermoregulation, neuroendocrine secretion, gastrointestinal and genitourinary functions, and plays a role in the control of vital functions [1]. It is a system that transmits impulses from the central nervous system to peripheral organs and is more effective. Thus, it controls the heart rate, the contractile force of heart, the contraction and dilatation of vessels, the contraction and relaxation of smooth muscles in various organs, and the secretion from the endocrine and exocrine glands.

ANS is anatomically and functionally divided into two as sympathetic and parasympathetic. The preganglionic fibers of parasympathetic nervous system (PSS) arise from the brainstem and are known as craniosacral fibers [2]. The vagus carries fibers to the heart, lungs, and other organs and forms the principal parasympathetic innervation of these organs. PSS causes a decrease in heart rate and blood pressure and is more concerned with the restoration and conservation of energy by increasing the digestion, absorption and excretion of nutrients [2].

The nuclei of sympathetic preganglionic nerve fibers are located in the sympathetic ganglion chain located in the lateral horns between T1-L2 of the spinal cord. Since the adrenal medulla is stimulated by sympathetic preganglionic fibers, adrenaline is released as a result of stimulation of nicotinic acetylcholine receptors. The neurotransmitter noradrenaline is found in the majority of postganglionic sympathetic nerve endings, in the adrenal medulla, and in the presynaptic terminal. Synthesis of adrenaline and noradrenaline in sympathetic postganglionic nerve endings and adrenal medulla is similar, but noradrenaline is converted to adrenaline more in the adrenal medulla [2].

The heart is under the control of sympathetic and parasympathetic nerves. A strong sympathetic stimulus can increase the normal heart rate from 70 beats per minute (bpm) in young individuals to approximately 250 bpm. Sympathetic stimuli can increase the volume of blood pumped and ejection pressure, increasing the force of heart contraction up to twice. The amount of blood pumped by the heart per minute (cardiac output) can increase by more than 100% with sympathetic stimulation.

Parasympathetic impulses, strong impulses of parasympathetic nerve fibers reaching the heart with the vagus nerves, can stop the heartbeat for a few seconds, and severe vagus impulses can reduce the force of contraction of the heart by 20-30% [3]. The vagus fibers radiate mainly to the atria rather than the ventricles, where strong contraction of the heart occurs. Therefore, vagus impulses reduce heart rate without significant reduction in cardiac contractility [3].

The rhythm produced due to spontaneous depolarization of the sinus node in the heart is called intrinsic heart rhythm [4]. Heart rate varies with age and gender. Hypoxia, exercise, and temperature are also among other factors that can affect intrinsic heart rate [5, 6]. Sympathetic and parasympathetic systems, which are the components of the autonomic system, are the main variables that affect the intrinsic heart rate.

## 2. Related Works

The first use of HRV information was made in 1965 by Hon. In his study, they showed that a difference was observed between each heartbeat before the visible changes in heart rate in babies in the womb [7]. HRV analyzes have an increasing importance in diagnostic use, especially in cardiology. Huikiri and Stein, and Zuern et al. demonstrated HRV knowledge as a risk assessment tool in patients with myocardial infarction recovery. In a large number of studies, it has been observed that the risk of mortality increases within a few years after myocardial infarction in patients with reduced or abnormal HRV [8, 9].

Studies have shown that patients with reduced HRV values are at risk of sudden cardiac death. When the researchers examined the records of healthy-looking people whose Electrocardiography (ECG) holter recordings were taken before their sudden death, they found that these people had low HRV values. Likewise, low HRV values were found in holter recordings taken just before the sudden death of angina patients [10, 11].

In many studies, it has been shown that the low SDNN value, which is one of the HRV time domain parameters, can be used as a tool to predict the mortality rate. Kearney et al. found that low SDNN value, low serum sodium content and high sodium creatinine amount indicate an increased risk of death. In the study of Nolan et al. on 433 patients, it was shown that the decreased SDNN value could predict death, not sudden death, in developing heart failure [12-14]. When the HRV values of the control group and the patient group with chronic heart failure were compared, it was observed that there was a significant difference between them. In addition, the low frequency spectral component of HRV was found to be associated with increased mortality in patients with chronic heart failure [15].

Today, in another study on HRV, 24-hour recordings were taken from participants between the ages of 20-70 to show the effect of age and gender on HRV, and when time domain analyzes were made, a decrease was observed in all parameters, especially in parasympathetic activity, due to aging. In other more detailed studies, it has been observed that parasympathetic activity decreases rapidly until the age of 80 and then increases again. In the same study, studies that showed decreased HRV in patients at risk of sudden cardiac death and low HRV values in healthy patients whose ECG holter records were examined before their sudden death were mentioned [16].

In a classification-based study in the form of HRV discrimination obtained from long-term measurements, records with normal sinus rhythm and records from PhysioBank of the patient with heart failure were used. Using long-term (24-hour) recordings of 54 patients with normal sinus rhythm (30 males, 24 females) and 29 heart failure patients (8 females, 2 males, 14 genders of the remaining 21 subjects unknown), aged 34-79 years, 9 different HRVs were used. The time domain parameter was calculated. As a result of the study, it was observed that the standard deviation (SDNN) parameter in 9 different long-term HRV measurements using linear discriminant analysis had the highest class discriminating power in the discrimination of diseased and healthy individuals [17].

Autonomic activity during sleep is assessed using spectral analysis of HRV. In the study, polygraphic recordings were taken from 11 healthy people during the night, and very low frequency, low frequency and high frequency components were evaluated. It was observed that the total spectrum power and very low frequency component were quite high in REM sleep, and the low frequency/high frequency ratio reflecting the sympathovagal balance reached its maximum value in REM sleep [18].

ECG recordings of 8 minutes under controlled breathing (12-15 breaths/minute) were taken from 202 patients aged 52±9 years with moderate and severe chronic heart failure. Decreased short-term LF power during controlled breathing when HRV analyzes are performed is a strong predictor of sudden death in patients with chronic heart failure and is independent of other variables [19].

In the studies, HRV was calculated based on the ECG signals of the person in stressful and non-stressful situations using different combinations of stress situations. In the study of Brunelli and Poggio, the mensa test was used to stress the person and ECG signals were taken throughout the experiment. As a result of time and frequency axis analysis, when mental activity state and resting state were compared, it was determined that the mean RR interval was lower and the pNN50 value was higher in the resting state. Although there was no significant difference in frequency axis analysis, there was an increase in the LF/HF ratio in the mental activity state [20]. The relationship between the stress caused by visual stimuli and HRV was examined and it was determined that significant changes occur in HRV in case of visual stress [21, 22].

In the study by Biel et al., the effects of external noise sounds on stress were investigated. Five different noise sounds, including car horn, baby crying, drill (drilling sound) and sounds from the construction site, were listened to 17 participants in the experiment. A total of 10 minutes of ECG recording was taken. In the first 1-minute part of the experiment procedure, the person was listened to a relaxing music and this part was accepted as the basic level. Then, after listening to each noise sound, there is a 1-minute rest period. As a result of the analysis, it was concluded that these noise sounds increase the stress level [23].

In the study of Mayya et al., which used PPG signals instead of ECG, PPG signals were obtained from 49 volunteers under two conditions. In the first case, the subject was asked to relax for 10 minutes and the signal was received for 4 minutes. In the second case, signals were recorded under five different situations that would put the person in a state of stress. These five situations are; Stroop color/word test, mental arithmetic test, memory test, public speaking test and counting backwards. Each stage took approximately 2 minutes. In addition, after each stage was completed, the subjects were asked to rate their stress levels between 1 and 5. The baseline was accepted as the lowest stress level and the scores from the subjects were averaged for each stage. As a result of the analyzes, it was examined whether there was a statistically significant difference between the baseline and each task, and it was seen that the RMSSD, pNN50, HF parameters, which are time and frequency domain analyzes, were statistically different in the baseline and in each stress condition [24].

In the study by Lu et al., which was conducted to compare HRV information obtained from ECG and PPG signals, 7 minutes of simultaneous ECG and PPG signals were recorded from 42 participants. Ag/AgCl electrodes were placed in lead-I arrangement for ECG recordings. For the PPG recording, the recording was taken from the left ear lobe. The 5-minute artifact-free portions of the recordings were used for analysis. The time and frequency domain parameters obtained from the analyzes were compared with each other with the help of statistical analysis methods. A correlation of over $r = 0.95$ was found between the parameters of both measurements. This shows that the measurement results are highly correlated with each other [25].

ECG and PPG signals were obtained from 19 healthy individuals and these signals were sampled at 250 and 500 Hz sampling rates, respectively in Selveraj et al. study. While the detection of R waves in the ECG signal is made with the Pan and Tompkins algorithm, the peaks of the PPG signal; signal scaling, thresholding, local peak detection, removal of detected very close peaks. When the values obtained from ECG and PPG signals were compared, it was seen that the lowest error occurred in SDNN with 2.46% and SD2 with 2% (reflecting long-term HRV in Poincare measurements), while the highest error occurred in pNN50 with 29.89%. In addition, pulses detected during PPG measurement do not contain high-frequency components associated with heartbeats, while ECG signals contain these features [26].

In the study of Taelman et al., the relationship between heart rate, HRV and mental stress was tried to be examined. Measurements taken from 28 participants were carried out in two stages, with and without mental testing for each subject. Mensa test was used for mental stress and ECG signals were taken throughout the experiment. As a result of time and frequency domain analysis, it was determined that the mean RR interval was lower when the mental activity state was compared with the resting state, and it was observed that the pNN50 value was higher in the resting state. Although there was no significant difference in frequency domain analysis, there was an increase in the LF / HF (low frequency / high frequency) ratio in the mental activity state [27].

In Wu and Lee, and Wu et al. studies, in which the relationship between stress caused by visual stimuli and HRV was examined, ECG signals were obtained from 50 participants. Signal acquisition phase was carried out in 2 parts. The first 5-minute period was the state of rest and no warning was applied to the subject. In the second 5 minutes, firstly, landscape pictures were shown for positive effect, and then black and white pictures were shown for visual stress. When the results were analyzed, it was seen that the RR intervals and the mean RR interval change in each different stimulus condition began to be wider when the subject was at rest, and narrower in the case of visual stress. Considering the frequency domain analysis, the average LF and HF power increased at the time of visual stress. Correspondingly, LF/HF was also increased, and significant changes in HRV were found under visual stress [28, 29].

In McDuff et al.'s study, data was collected by digital camera recording using a slightly different method in the signal collection stage for the measurement of stress. With a camera placed 3 m away from the person, a camera that can capture the effect of stress on the person's breathing and HRV was used. As a reference, blood volume pulses and electrodermal activity were obtained with the help of a finger sensor, and respiratory information was obtained by wearing a chest strap. 7 female 3 male 10 participants participated in the experiment. During the first two minutes, the signal was received while the participants were relaxed, then they were asked to count backwards from 4000 by subtracting 7 each time, and the signal was taken in this way for a while. These physiological signals and camera recordings were taken synchronously and then the results were compared. When the camera recordings and the physiological records used as reference are compared after the experiment, the relationship between them is $r=1$ for heart rate, $r= 0.93$ for respiration, $r= 0.93$ for HR LF power, $r= 0.93$ for HF, for LF/HF $r=0.93$ and $p<0.01$ were found [30].

In the study of Wang and Wang, which aimed to evaluate stress and emotion over HRV, ECG signals were obtained from 26 participants. In order to induce emotion in people, 3 types of movies were prepared for fear, relaxation and happiness, each of which is between 3-10 minutes. The picture matching game was used to complete the task in the appropriate time for the stress situation. In addition, to validate the induction of appropriate emotional information, subjects rated their emotional state using a Likert scale. When the results were analyzed, there was a decrease in the RR intervals in the 4 different mood states compared to the calm state. Heart rate in fear and stress increased more than in relaxation and happiness. SDNN index short interval changes of HRV under negative emotion (fear, stress) were higher than positive mood. In addition, the pNN50 value, which indicates vagus nerve activity, was suppressed under stress [31].

One study examined changes in sleep after supramaximal activity. It was observed that the duration of HRV at night of activity was shortened, and HRV values returned to normal only after two days [32]. In another study, recovery in HRV after single and multiple (4 times) WanT administration was examined after 20 minutes, 1 hour and 2 hours; It was observed that HRV values decreased more after multiple WanT applications, and resting HRV results could not be achieved in both applications after two hours [33].

In a study, the effect of short-term submaximal cycling ergometer loading on HRV recovery in different body positions (sitting, lying down, lying with feet up) was examined and HRV was greater in supine positions during a 15-minute rest period, but HRV decreased to resting values in all three positions. It was understood that it could not be reached completely [34]. There are also studies on other factors that affect HRV recovery. In a study examining the effects of pre-exercise energy drink and alcohol intake on HRV, lower HRV values were achieved after exercise in groups receiving alcohol and energy drinks [35].

Ten male swimmers in the 13-14 age group, who were athletes in a special swimming team in Ankara, voluntarily participated in the research. The mean age of the participants was 13.40 ± 0.52 years, their height was 168.70 ± 8.35 cm, their body weight was 59.56 ± 11.86 kg, and their body fat ratio was 14.51 ± 5.69%. The aim of this study was to examine the change in HRV parameters after 50 m sprint swimming activity and to understand the effect of ANS on the heart. As a result of the research, it was observed that high-intensity and short-term 50 m sprint swimming activity affected the sympathovagal balance by increasing the sympathetic activity on the heart and decreasing the vagal effect [36].

In a cross-sectional study by Ulu et al., 28 patients under dialysis treatment and 30 healthy controls were compared in terms of HRV. HRV was evaluated with 24-hour Holter electrocardiography. HRV was found to be significantly lower in patients with chronic renal failure under dialysis treatment compared to the control group (SDNN and pNN50 values were 95.4±31.5, 127.5±38.8, p=0.001 and 8.3±6.1, respectively). 16±9; p=0.71) [37].

The contributions of the paper are as follows:

- None of the studies in literature are real-time. In all studies, data were first taken and then analyzed in the computer environment.
- In our study, reading and analysis of the data was done with Raspberry Pi 4 microcomputer. No normal computer was used anywhere. Python codes work easily on Raspberry Pi 4 microcomputer. We aim to produce a prototype with this study. For this purpose, a very small, portable, battery-powered hardware was preferred by disabling the computer.

## 3. Material and Method

### 3.1 PPG Signal

PPG signal measurement is a noninvasive, electro-optical method that provides information about the volume of blood flowing at a test site of the body close to the skin. A PPG signal is obtained by light that illuminates the relevant area of body and then reflects or passes through that area [38]. The PPG signal is produced by the periodic beating of the heart. The waveform and characteristic parameters of a typical PPG signal are given in Figure 1.

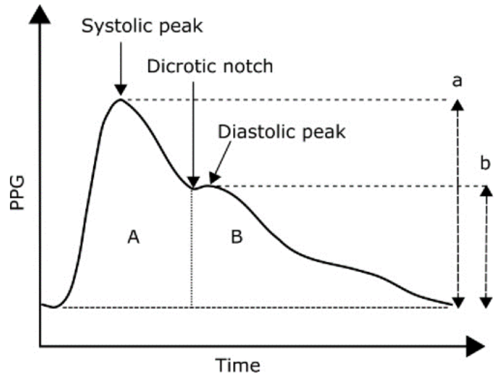
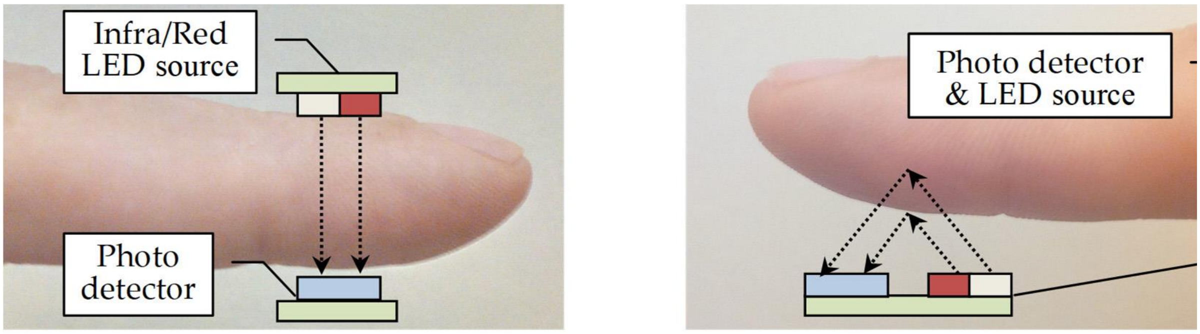



Figure 1 PPG Signal Waveform [39]

PPG signals are received optically from the body with the help of sensors with a light source and photodiode. PPG signals can be obtained by two different finger-type probes including transmissive and reflection modes, respectively as shown in Figure 2.




(a) (b)

Figure 2 Finger-type PPG probes in (a) transmission (b) reflection modes [40]

In transmission mode sensor shown in Figure 2(a), the emitting LED and receiving photodiode are positioned opposite each other. This type of sensor can be used in areas of the body where light transmittance is high, such as fingertips and earlobes. Each time the heart pumps blood to the body, the blood density at the fingertip changes accordingly. Depending on the change in blood density, the intensity of the light sent from one surface of finger, reaching the opposite, also changes. As the blood density increases, the light intensity reaching the photodiode on the opposite side decreases. When the blood is drawn from the capillaries, the light intensity reaching the opposite side increases. Depending on this change, the light intensity on the photodiode changes and the PPG signal occurs [41].

In reflection mode sensor in Figure 2(b), the receiver and transmitter are positioned in the same direction. This type of sensor is used in areas of the body with low light transmission. In this sensor, unlike the transmission mode sensor, when the blood density increases, the amount of reflection will be higher, and the light intensity falling on the photodiode will increase. When the blood is withdrawn from the vessels, the light intensity falling on the photodiode will be less since the amount of reflection will decrease. As a result of this change in blood density, the PPG signal is obtained [41].

### 3.2 Heart Rate Variability

Heart Rate Variability (HRV) defines the change between heart beats based on the acceleration of heart rhythm with the activation of sympathetic nervous system and the slowing of heart rhythm with the activation of parasympathetic nervous system. Multiple methods are available to evaluate autonomic nervous system activity. These methods are; measurement of adrenaline and noradrenaline in the urine [42], measurement of muscle sympathetic activity [43] or HRV. Among these methods, the most preferred and reliable measurement is HRV.

HRV indicates synchronization between heartbeats. HRV increases when heartbeats are irregular, and HRV decreases if heartbeats are fairly regular. Analysis of HRV is a reliable and non-invasive method for assessing autonomic regulatory responses. This measurement technique is not only used to reveal autonomous function changes. It can also provide information about the prognosis of some diseases or the probability of a healthy person becoming sick in the future.

In this context, HRV provides information about the autonomic regulation of heart via the parasympathetic and sympathetic nervous systems [44]. In healthy individuals, HRV has a circadian rhythm. It increases at night and decreases during the day. A decrease in HRV is accepted as an indicator of a decrease in parasympathetic activity and an increase in sympathetic activity [45]. In clinical studies conducted in this context, showing psychosomatic symptoms; HRV has been reported to be reduced in individuals with chronic fatigue syndrome [46] anxiety and depression [47] and work stress [48]. PPG and RR intervals should be recorded for a certain period of time to determine HRV. Various algorithms can be used to calculate HRV, from simple statistical methods to complex non-linear mathematical methods [2].

### 3.3 HRV Time Domain Parameters

Measurement of time-domain variables is evaluated by statistical calculation of variables in RR intervals [45]. By looking at the intervals between consecutive QRS complexes on a 24-hour Electrocardiography (ECG), heart rate or the distance between consecutive normal complexes (normal-normal (NN) intervals) is determined. From these records, various parameters such as mean NN interval, difference between longest and shortest NN interval, average heart rate can be calculated. In time-domain measurements, necessity of taking long sections of 24 hours and providing standard conditions causes a decrease in patient compliance [49].

In this study, HRV vector was created depending on the time between these points, along with the peaks detected from the filtered PPG signal. The mean and standard deviation values of created vector were determined and five different time domain parameters (SDNN, SDSD, RMSSD, PNN20 and PNN50) were extracted.

RMSSD is the square root of mean of the square of the RR interval differences. This measurement estimates the high frequency components of heart rate in short-term normal-to-normal recordings that reflect a parasympathetic regulation of the heart. A decrease in RMSSD (below 10) associated with a low SDNN (below 20) is associated with the risk of developing cardiac disease [49]. SDSD is the standard deviation of the adjacent RR interval differences [36]. pNN50 is the proportionality coefficient obtained by dividing the total number of RR intervals by NN50 [36]. pNN20 is the ratio obtained by dividing pNN20 by the total number of NNs [36].

SDNN is the standard deviation of the time (NN) between successive QRS complexes on ECG signal and reflects all cycle components responsible for variability throughout the recording. SDNN is affected by the recording time and values decrease as the recording time decreases and increase as it increases. Short-term (5min) recordings reflect high-frequency changes, while long-term (24-hour) recordings reflect low-frequency changes. Therefore, it would not be correct to compare SDNN values in long and short-term records. SDNN covers the time from the beginning to the end of the ECG signal recording and the times should be standardized [49]. The formulas of HRV time domain parameters used in the study are given in Table 1.

Table 1 HRV Time Domain Parameters

| **HRV Time Domain Parameters (Abbreviations)** | **HRV Time Domain Parameters (Full Forms / Description)** | **Formulas** |
|---|---|---|
| SDNN | Standard deviation of NN intervals | $\sqrt[2]{\frac{1}{N-1}\sum_{j=1}^{N}\left(RR_j - RR\right)^2}$ |
| SDSD | Standard deviation of the differences between successive NN intervals | $\sqrt[2]{\frac{1}{N-1}\sum_{j=1}^{N-1}\left(\lvert RR_j - RR_{j+1}\rvert - RR_{dif}\right)^2}$ |
| RMSSD | Root mean square of successive RR interval differences | $\sqrt[2]{\frac{1}{N-1}\sum_{j=1}^{N-1}\left(RR_{j+1} - RR_j\right)^2}$ |
| PNN20 | Percentage of successive RR intervals that differ by more than 20 ms | $\frac{NN20}{N-1} \times 100\%$ |
| PNN50 | Percentage of successive RR intervals that differ by more than 50 ms | $\frac{NN50}{N-1} \times 100\%$ |

### 3.4 MAX30100 Pulse Oximeter and Heart Rate Sensor Module

MAX30100 pulse oximeter and heart rate sensor is an optical sensor that takes readings from emitting two wavelengths of light from two LEDs (Red (650 nm) and Infrared (IR) (950 nm)) and then measures its absorption in the bloodstream against a photodetector. The MAX30100 sensor works on the principle of reflection mode sensor (See in Figure 2(b)). In the reflection sensor, as the amount of reflection increases when blood density increases, the light intensity falling on photodiode will increase. When the blood is withdrawn from the vessels, the light intensity falling on photodiode will be less since the amount of reflection will decrease. As a result of this change in blood density, the PPG signal is obtained [41]. This particular LED color combination is optimized for reading data from the fingertip. The signal is processed by a low noise analog signal processing unit and transmitted to the target MCU via the mikroBUS I$^2$C interface. The MAX30100 sensor and system block diagram of sensor are shown in Figures 3 and 4, respectively.


Figure 3 MAX30100 Pulse Oximeter and Heart Rate Sensor Module [50]

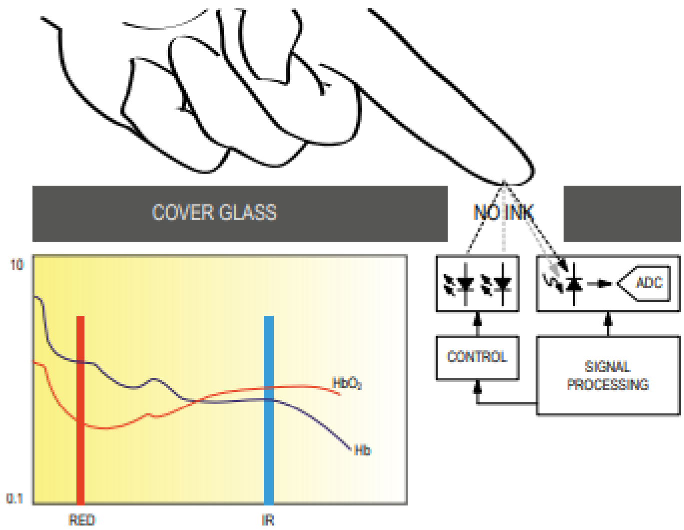



Figure 4 MAX30100 System Block Diagram [51]

In the working principle of MAX30100 sensor, DC and AC components belonging to the PPG signal are obtained through the sensor. In the MAX30100 sensor, a heart rate data sample consists of only one IR data point, so the received PPG signal for heart rate is obtained as a single wavelength signal.

### 3.5 Raspberry Pi 4 Complete Starter Kit

Raspberry Pi is a single board computer. This means that all units required for a computer such as processor, RAM memory, inputs/outputs are gathered on a single circuit board. Thanks to its small design and compact structure, it is possible to use these computers such as in robotic projects, smart home systems, embedded systems, kiosks, and even as desktop computers by connecting peripherals such as keyboard/mouse and screen. In addition to Linux operating systems, Raspberry Pi has the ability to run many ready-made systems specially developed to perform functions such as game machine, media center, network device. Raspberry Pi 4 model used in the study available in Complete Starter Kit is illustrated in Figure 5.

Figure 5. Raspberry Pi 4 Microcomputer [52]

## 4. Results and Discussion

Raspberry Pi 4, WaveShare LCD display, MAX30100 sensor and powerbank connections were established and the system was started. System setup connections are shown in Figure 6(a) and Figure 6(b).

(a) (b)

Figure 6 System setup connections (a) combining system elements (b) adding MAX30100 sensor to the system

Python software version 3.7.3 was installed on Raspberry Pi 4 microcomputer. The necessary libraries were downloaded for the study.

### 4.1 Data Collection and Analysis

PPG signals were obtained from left index finger by placing the finger horizontally on the sensor from a 24-year-old male volunteer while he was at resting state in stressful and outdoor environments. In a study for HRV analysis, PPG signals were obtained from the subject over a 10-minute period [53]. In this study, 11 minutes of PPG signals were recorded by taking this information as a reference. While the PPG signal is being received, the lack of contact of the finger for 1 minute out of 11, when the finger touches the sensor, motion artifacts can affect the accuracy and sensitivity of the received data. For this reason, HRV detection was performed by processing the signals outside the first 1 minute portion during signal processing. In all cases where the signal is received, the volunteer is in a sitting position.

Two Python code files were written to read and analyze the data. The signals were first read with the readdata.py file and saved in separate outdoordata.csv and stressdata.csv files. Then, this .csv files was analyzed in the analysis code (analysis.py) and the HRV time domain attributes were extracted for each case.

### 4.2 Data Preprocessing

In this study, a finger type heart rate sensor (MAX30100) was used to calculate heart rate. Finger heart rate sensor has one IR transmitter and one IR receiver. It works on the basis of detecting the amount of light sent by the transmitter as it passes through the finger, depending on the pulse value. After detecting the IR beam passing through fingertip, the resulting signal is amplified by two operational amplifiers. A pulse is then generated by a comparator. The pulse size is calculated by reading the produced pulse with microcomputer. While finding the impact length, empty and full parts of the impact are calculated separately and the impact length is found from the sum of the two. There is a transition time from the peak value to the trough value. Then, the number of times this pulse length occurs in a minute is found and the pulse is calculated [54].

Communication between MAX30100 sensor and Raspberry Pi 4 microcomputer is provided by $I^2C$ communication protocol. According to this communication protocol, the ground line between master and slave must be common, while the SDA (serial data, data line) and SCL (serial clock, clock pulse line used for data synchronization) pins must match. While data synchronization is provided on the SCL line, bidirectional data flow takes place on the SDA line. Digital data is stored in a 16-bit FIFO (first in first out). The $I^2C$ communication protocol allowed this data to be shared between the two systems [55]. The MAX30100 uses 1.8V and 3.3V power supplies, and the negligible standby current can be turned off via software, ensuring the power supply stays connected at all times. It has programmable high sampling rate and LED current feature [51]. The MAX30100 configuration settings set in the firmware of the Raspberry Pi 4 microcontroller are given in Table 2.

Table 2 MAX30100 Sensor Configuration Settings

| **Settings** | **Value** |
|---|---|
| Mode Control | Heart Rate Mode (IR) |
| Heart Rate sampling rate control | 100 sample per second |
| LED Pulse Width Control | 400 μs (14 bit) |

Filtering processes were performed to strengthen the weak signal data contained in the raw PPG signal, and to remove the noise from the external environment. Bandpass filter codes were used while filtering the signal. The frequency range applied for this filter was chosen as 0.8 Hz - 2.5 Hz. While selecting these frequency ranges, the highest (150 bpm) and lowest (48 bpm) pulse values were selected and the process was performed. These transactions are;

The lowest frequency value that the filter will pass = 48(bpm)/60(second) = 0.8 Hz

The highest frequency value passed by the filter = 150(bpm)/60(second) = 2.5 Hz

In stressful environment, PPG signals were obtained from a 24-year-old male volunteer through the MAX30100 sensor. The received PPG signal data is saved in the stressdata.csv file. In Figure 7, the raw PPG signal formed from the recorded data is given.

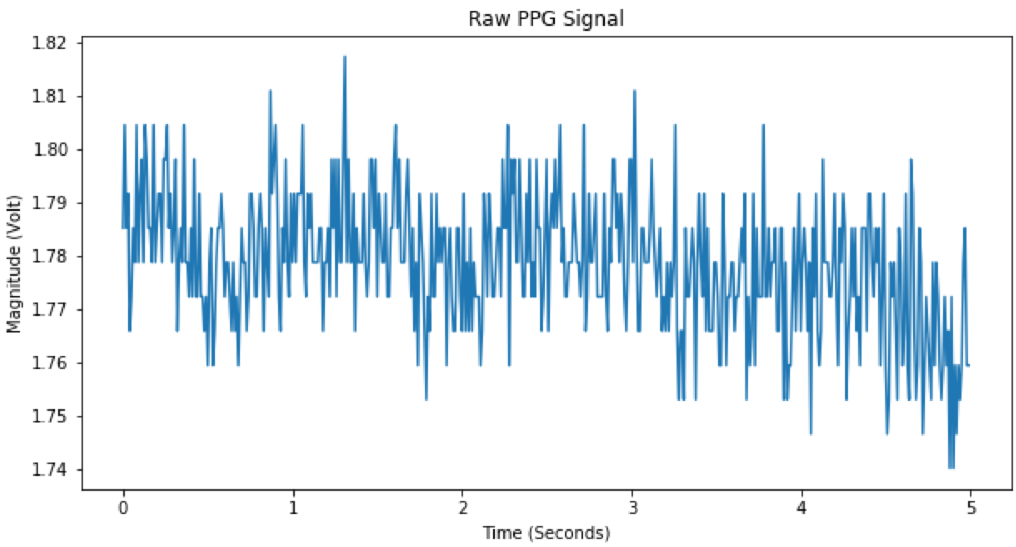



Figure 7 Raw PPG signal from stressdata.csv file

The signal obtained as a result of filtering the received PPG signals to remove noise and motion artifacts is shown in Figure 8.

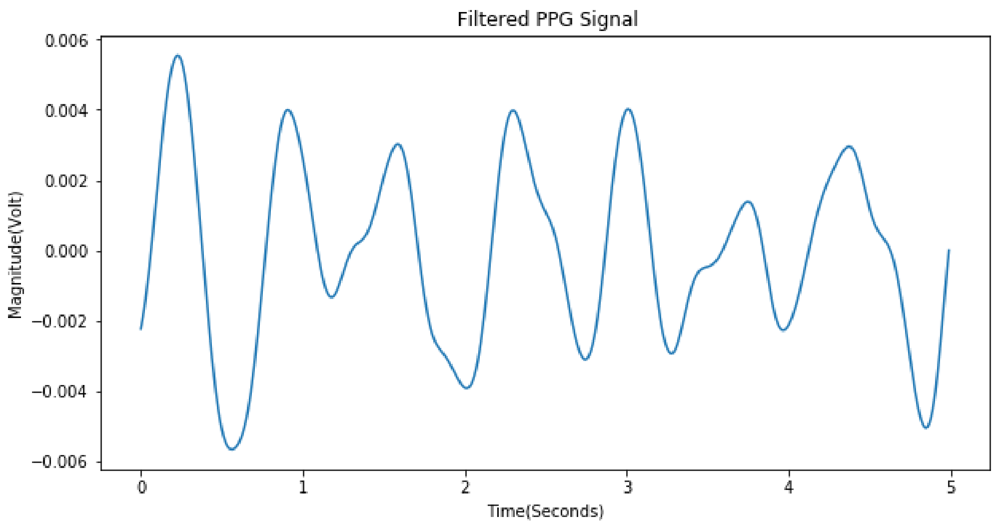



Figure 8 Filtered PPG signal from stressdata.csv file

The peaks and outlier removal of the filtered single-wavelength PPG signal received in the stress state of a 24-year-old male individual are given in Figure 9.

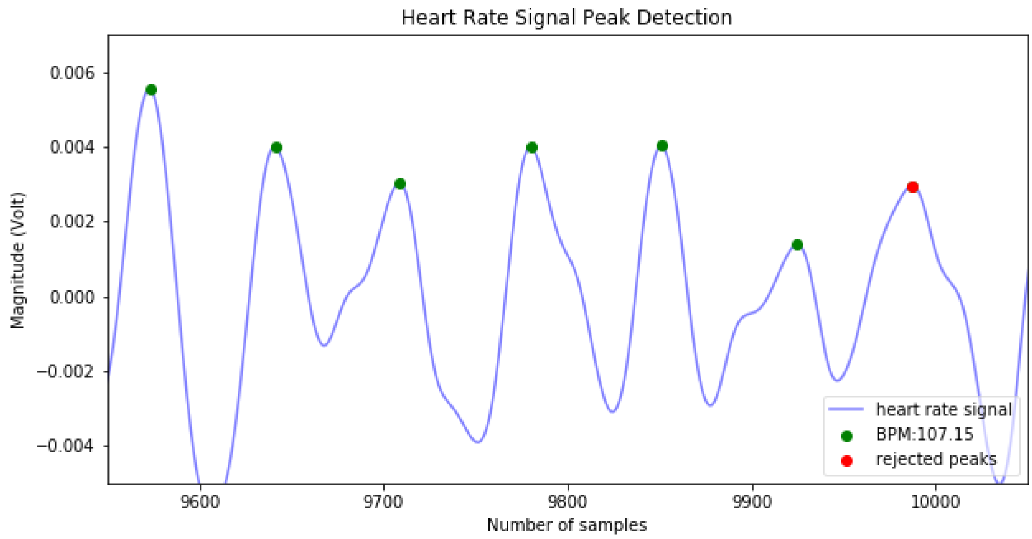



Figure 9 PPG signal peak detection from stressdata.csv file

In outdoor environment, PPG signals were obtained from a 24-year-old male volunteer through the MAX30100 sensor. The received PPG signal data is saved in the outdoordata.csv file. In Figure 10, the raw PPG signal formed from the recorded data is given.

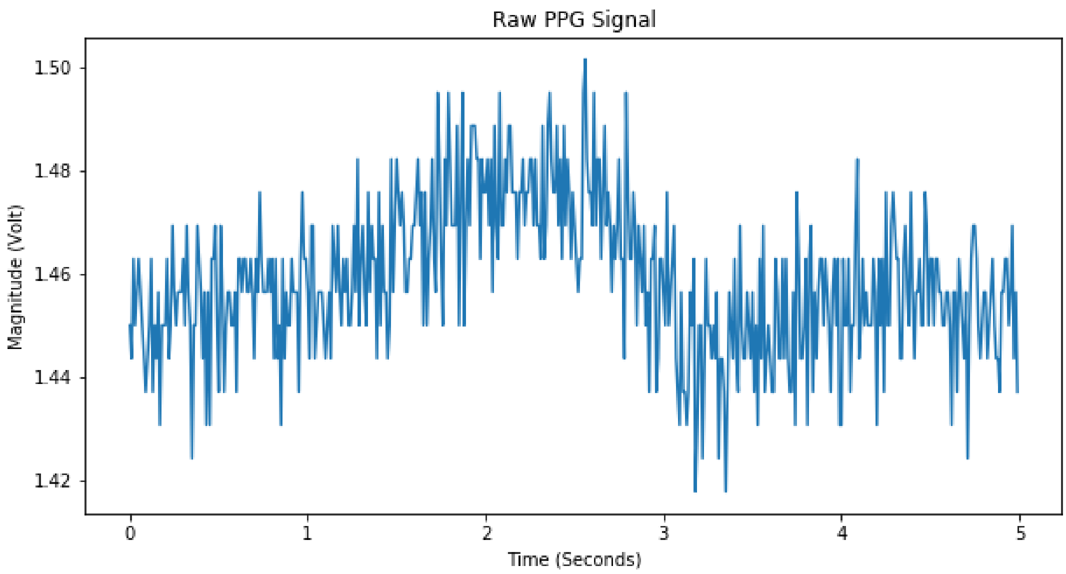



Figure 10 Raw PPG signal from outdoordata.csv file

The signal obtained as a result of filtering the received PPG signals to remove noise and motion artifacts is given in Figure 11.

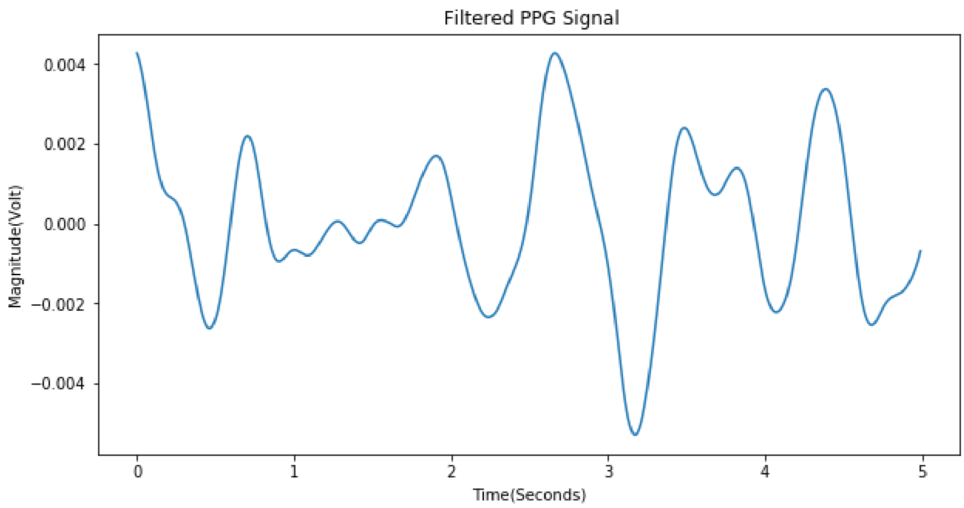



Figure 11 Filtered PPG signal from outdoordata.csv file

The peaks and outlier removal of the filtered single-wavelength PPG signal received in the outdoor state of a 24-year-old male individual are shown in Figure 12.

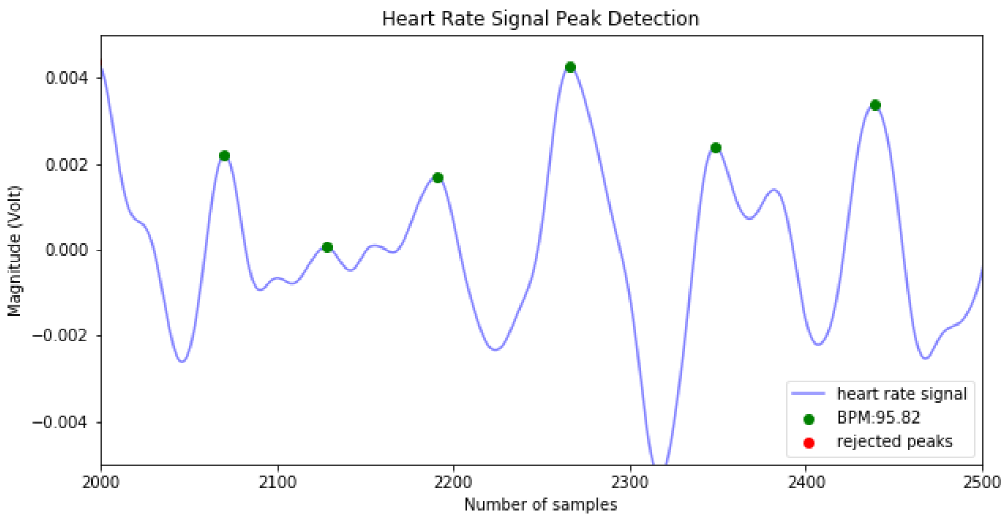



Figure 12 PPG signal peak detection from outdoordata.csv file

## 4.3 Feature Extraction

The heartpy library from Python libraries was used to obtain HRV time domain features (SDNN, SDSD, RMSSD, pNN20 and pNN50) after signal processing. In this study, PPG method was used to determine HRV. This method allowed us to interpret the heart HRV information as a result of filtering the 10-minute portion of the received PPG signals for 11 minutes under different conditions from MAX30100, a non-invasive photodiode heart rate sensor, finding the peaks and obtaining the time domain features.

A decrease in HRV is accepted as an indicator of a decrease in parasympathetic activity and an increase in sympathetic activity [45]. In clinical studies conducted in this context, showing psychosomatic symptoms; HRV has been reported to decrease in individuals with chronic fatigue syndrome, anxiety and depression, and work stress [46-48].

Analysis results of 2 different cases (stress status and outdoor environment) are given in Table 3. The HRV is basically based on SDNN.

Table 3 Time domain features of PPG signal received from a 24-year-old male in two cases

| **Cases** | **Pulse (bpm)** | **SDNN (ms)** | **SDSD (ms)** | **RMSSD (ms)** | **PNN20 (%)** | **PNN50 (%)** |
|---|---|---|---|---|---|---|
| Stress Status (Mental Activity Intense, Worry, Anxiety) | 107.15 | 126.42 | 37.28 | 66.20 | 0.76 | 0.47 |
| Outdoor (Calm, Relaxed, No Anxiety) | 95.82 | 159.85 | 44.49 | 84.41 | 0.79 | 0.63 |

As a result of the study, it was observed that stress and anxiety decreased SDNN, while outdoor environment increased SDNN. These results are consistent with the results in the literature.

## 5. Conclusion

Today, it is obvious that the immune system should be strong when fighting epidemics. In this study, the detection of HRV, which is an indicator of the immune system, was performed non-invasively using the PPG signal. The important point here is to determine which situations reduce HRV actually one of the time domain parameters, SDNN. It is a fact that we should stay away from environments that decrease SDNN, and engage in environments, situations, emotions and mental activities that increase SDNN. In fact, we have scientifically proven a fact known by the society. SDNN decreases in cases of anxiety, depression, being in closed environments, psychosomatic symptoms, chronic fatigue syndrome, and mental thoughts, but being in a relaxed mind in nature has an effect that increases SDNN.

In future studies, it is possible to use MAX30100 and MAX30102 sensors to study more mental activity, emotional states and receiving signals in different environments, and how the environments, emotions and mental activities in human life affect our health and immune system.

## Acknowledgments

This research has been supported by Scientific Research Projects Commission of Zonguldak Bulent Ecevit University, Turkey, under Project Number: 2020-39971044-02. We would also like to thank Abdelgader Obeida, Dilan Pişkin and İhsan Acuz for valuable contribution to the study.

## References

[1] E. E. Benarroch, "The central autonomic network: functional organization, dysfunction, and perspective," In Mayo Clinic Proceedings, vol. 68, no. 10, pp. 988-1001, 1993.

[2] J. V. Freeman, F. E. Dewey, D. M. Hadley, J. Myers and V. F. Froelicher, "Autonomic nervous system interaction with the cardiovascular system during exercise," Progress in Cardiovascular Diseases, vol. 48, no. 5, pp. 342-362, 2006.

[3] J. E. Hall, Guyton ve Hall Tıbbi Fizyoloji. İstanbul, Güneş Tıp Kitabevi, 2017.

[4] M. K. Lahiri, P. J. Kannankeril and J. J. Goldberger, "Assessment of autonomic function in cardiovascular disease: physiological basis and prognostic implications," Journal of the American college of Cardiology, vol. 51, no. 18, pp. 1725-1733, 2008.

[5] A. D. Jose and F. Stitt, "Effects of hypoxia and metabolic inhibitors on the intrinsic heart rate and myocardial contractility in dogs," Circulation research, vol. 25, no. 1, pp. 53-66, 1969.

[6] A. D. Jose, F. Stitt and D. Collison, "The effects of exercise and changes in body temperature on the intrinsic heart rate in man," American heart journal, vol. 79, no. 4, pp. 488-498, 1970.

[7] E. H. Hon, " Electronic evaluations of the fetal heart rate patterns preceding fetal death, further

observations," Am J Obstet Gynecol, vol. 87, no. 1, pp. 814-826, 1965.

[8] H. V. Huikuri and P. K. Stein, " Clinical application of heart rate variability after acute myocardial infarction," Frontiers in physiology, vol. 3, no. 41, pp. 1-5, 2012.

[9] C. S. Zuern, P. Barthel and A. Bauer, "Heart rate turbulence as risk-predictor after myocardial infarction," Frontiers in physiology, vol. 2, no. 99, pp. 1-8, 2011.

[10] H. Mølgaard, K. E. Sørensen and P. Bjerregaard, "Attenuated 24-h heart rate variability in apparently healthy subjects, subsequently suffering sudden cardiac death," Clinical Autonomic Research, vol. 1, no. 3, pp. 233-237, 1991.

[11] A. Pozzati, L. G. Pancaldi, G. Di Pasquale, G. Pinelli and R. Bugiardini,"Transient sympathovagal imbalance triggers “ischemic” sudden death in patients undergoing electrocardiographic Holter monitoring," Journal of the American College of Cardiology, vol. 27, no. 4, pp. 847-852, 1996.

[12] M. T. Kearney et al., " Predicting death due to progressive heart failure in patients with mild-to-moderate chronic heart failure," Journal of the American College of Cardiology, vol. 40, no. 10, pp. 1801-1808, 2002.

[13] M. Efeoğlu, "Acil Tıp Eğitimi İçin EKG, EKG Kütüphanesi," 2014. [Online]. Available: https://acilci.net/kategori/tibbi-kategoriler/kardiyoloji/ekg/litfl-ekg-kutuphanesi/. [Accessed: 14-Oct-2021].

[14] J. Nolan et al.,"Prospective study of heart rate variability and mortality in chronic heart failure: results of the United Kingdom heart failure evaluation and assessment of risk trial (UK-heart)," Circulation, vol. 98, no. 15, pp. 1510-1516, 1998.

[15] S. Guzzetti, R. Magatelli, E. Borroni and S. Mezzetti, "Heart rate variability in chronic heart failure," Autonomic neuroscience, vol. 90, no. 1-2, pp. 102-105, 2001.

[16] B. Xhyheri, O. Manfrini, M. Mazzolini, C. Pizzi and R. Bugiardini, "Heart rate variability today," Progress in cardiovascular diseases, vol. 55, no. 3, pp. 321-331, 2012.

[17] M. H. Asyali, "Discrimination power of long-term heart rate variability measures," Proc. - 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 200-203, 2003.

[18] P. Bušek, J. Vaňková, J. Opavský, J. Salinger and S. Nevšímalová, "Spectral analysis of heart rate variability in sleep," Physiol res, vol. 54, no. 4, pp. 369-376, 2005.

[19] M. T. La Rovere et al., " Short-term heart rate variability strongly predicts sudden cardiac death in chronic heart failure patients," Circulation, vol. 107, no. 4, pp. 565-570, 2003.

[20] R. Brunelli and T. Poggio, “Face recognition: Features versus templates,” IEEE transactions on pattern analysis and machine intelligence, vol. 15, no. 10, pp. 1042-1052, 1993.

[21] A. Samal and P. A. Iyengar, “Automatic recognition and analysis of human faces and facial expressions: A survey,” Pattern recognition, vol. 25, no. 1, pp. 65-77, 1992.

[22] D. Dumn, “Using a multi-layer perceptron neural for human voice identification,” Proc. - 4th Int. Conf. Signal Process. Applicat. Technol., 1993.

[23] L. Biel, O. Pettersson, L. Philipson and P. Wide, “ECG analysis: a new approach in human identification,” IEEE Transactions on Instrumentation and Measurement, vol. 50, no. 3, pp. 808-812, 2001.

[24] S. Mayya, V. Jilla, V. N. Tiwari, M. M. Nayak and R. Narayanan, " Continuous monitoring of stress on smartphone using heart rate variability," Proc. - 15th IEEE International Conference on Bioinformatics and Bioengineering, pp. 1-5, 2015.

[25] G. Lu, F. Yang, J. A. Taylor and J. F. Stein, " A comparison of photoplethysmography and ECG recording to analyse heart rate variability in healthy subjects," Journal of medical engineering & technology, vol. 33, no. 8, pp. 634- 641, 2009.

[26] N. Selvaraj, A. Jaryal, J. Santhosh, K. K. Deepak and S. Anand, "Assessment of heart rate variability derived from finger-tip photoplethysmography as compared to electrocardiography," Journal of medical engineering & technology, vol. 32, no. 6, pp. 479-484, 2008.

[27] J. Taelman, S. Vandeput, A. Spaepen ans S. Van Huffel, "Influence of mental stress on heart rate and heart rate variability," Proc. - 4th European conference of the international federation for medical and biological engineering, pp. 1366-1369, 2009.

[28] W. Wu and J. Lee, "Development of full-featured ECG system for visual stress induced heart rate variability (HRV) assessment," Proc. - 10th IEEE International Symposium on Signal Processing

and Information Technology, pp. 144-149, 2010.

[29] W. Wu, J. Lee and H. Chen, " Estimation of heart rate variability changes during different visual stimulations using non-invasive continuous ecg monitoring system," Proc. - International Joint Conference on Bioinformatics, Systems Biology and Intelligent Computing, pp. 344-347, 2009.

[30] D. McDuff, S. Gontarek and R. Picard, "Remote measurement of cognitive stress via heart rate variability," Proc. - 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pp. 2957-2960, 2014.

[31] C. Wang and F. Wang, "An emotional analysis method based on heart rate variability," Proc. - IEEE-EMBS International Conference on Biomedical and Health Informatics, pp. 104-107, 2012.

[32] P. B. Laursen, A. Said and B. Martin, "Nocturnal heart rate variability following supramaximal intermittent exercise," International Journal of Sports Physiology and Performance, vol. 4, no. 4, pp. 435-447, 2009.

[33] P. J. Millar, M. Rakobowchuk, N. Mccartney and M. J. Macdonald, " Heart rate variability and nonlinear analysis of heart rate dynamics following single and multiple Wingate bouts," Applied Physiology, Nutrition & Metabolism, vol. 34, no. 5, pp. 875-883, 2009.

[34] O. F. Barak, D. G. Jakovljevic, J. Z. P. Gacesa, Z. B. Ovcin, D. A. Brodie and N. G. Grujic, " Heart rate variability before and after cycle exercise in relation to different body positions," Journal of sports science & medicine, vol. 9, no. 2, pp. 176-182, 2010.

[35] U. Wiklund, M. Karlsson, M. Ööström and T. Messner, " Influence of energy drinks and alcohol on post-exercise heart rate recovery and heart rate variability," Clinical physiology and functional imaging, vol. 29, no. 1, pp. 74-80, 2009.

[36] D. Aras, F. Akça and C. Akalan, "50 metre sprint yüzmenin 13-14 yaşlarındaki erkek yüzücülerde kalp hızı değişkenliğine etkisi," Spormetre Beden Eğitimi ve Spor Bilimleri Dergisi, vol. 11, no. 1, pp. 13-18, 2013.

[37] R. Ulu, N. Gözel, İ. P. Yiğit, Z. Kemeç, K. A. Uğur, O. Doğdu and A. Doğukan, " Diyaliz Modalitelerinin Kalp Hızı Değişkenliği Üzerine Olan Etkisi," Türk Nefroloji Diyaliz ve Transplantasyon Dergisi, vol. 26, no. 1, pp. 93-97, 2017.

[38] A. F. Aleixo, E. G. Lima, É. C. Leite, A. V. Inocêncio, L. T. Lins and M. A. Rodrigues, "Wearable Device for Acquisition of SpO 2 and Heart Rate," Proc. - XXVI Brazilian Congress on Biomedical Engineering, pp. 577-582, 2019.

[39] M. Paul, A. F. Mota, C: H. Antink, V. Blazek and S. Leonhardt, " Modeling photoplethysmographic signals in camera-based perfusion measurements: optoelectronic skin phantom," Biomedical optics express, vol. 10, no. 9, pp. 4353-4368, 2019.

[40] J. Přibil, A. Přibilová and I. Frollo, "Comparative Measurement of the PPG Signal on Different Human Body Positions by Sensors Working in Reflection and Transmission Modes," In Engineering Proceedings, vol. 2, no. 69, pp. 1-7, 2020.

[41] Ö. Yıldırım, Kalp aritmisinin çift dalgaboylu PPG sinyalleri kullanılarak belirlenmesi, Master Thesis, Dept. of Electrical and Electronics Engineering, Graduate Institute of Natural and Applied Sciences, Karadeniz Teknik University, Trabzon, Turkey, 2017.

[42] D. S. Goldstein, R. McCarty, R. J. Polinsky and I. J. Kopin, "Relationship between plasma norepinephrine and sympathetic neural activity," Hypertension, vol. 5, no. 4, pp. 552-559, 1983.

[43] B. G. Wallin and N. Charkoudian, " Sympathetic neural control of integrated cardiovascular function: insights from measurement of human sympathetic nerve activity," Muscle & nerve, vol. 36, no. 5, pp. 595-614, 2007.

[44] T. B. Kuo and C. C. Yang, "Altered frequency characteristic of central vasomotor control in SHR," American Journal of Physiology-Heart and Circulatory Physiology, vol. 278, no. 1, pp. H201-H207, 2000.

[45] A. H. Marques, M. N. Silverman and E. M. Sternberg, "Evaluation of stress systems by applying noninvasive methodologies: measurements of neuroimmune biomarkers in the sweat, heart rate variability and salivary cortisol," Neuroimmunomodulation, vol. 17, no. 3, pp. 205-208, 2010.

[46] R. Freeman and A. L. Komaroff, "Does the chronic fatigue syndrome involve the autonomic nervous system?" The American journal of medicine, vol. 102, no. 4, pp. 357-364, 1997.

[47] J. W. Hughes and C. M. Stoney, " Depressed mood is related to high-frequency heart rate variability during stressors," Psychosomatic medicine, vol. 62, no. 6, pp. 796- 803, 2000.

[48] T. Chandola, A. Heraclides and M. Kumari, " Psychophysiological biomarkers of workplace stressors," Neuroscience & Biobehavioral Reviews, vol. 35, no. 1, pp. 51-57, 2010.
[49] S. Açıkgöz and E. Diker, "Kalp hızı değişkenliği," MN Kardiyoloji, vol. 3, no. 1, pp. 275-278, 1996.
[50] "MAX30100 Chip Heart Rate Sensor Module," 2021. [Online]. Available: https://www.alibaba.com/product-detail/MAX30100-chip-heart-rate-sensor-module_1600142413057.html. [Accessed: 24-June-2021].
[51] "Maxim Integrated MAX30100 Datasheet," 2021. [Online]. Available: https://datasheets.maximintegrated.com/en/ds/MAX30100.pdf. [Accessed: 24-June-2021].
[52] "Raspberry Pi 4 Model B 4GB RAM Completely Upgraded," 2021. [Online]. Available: https://www.alibaba.com/product-detail/Raspberry-Pi-4-Model-B-4GB_1600081890613.html [Accessed: 24-June-2021].
[53] D. Yılmaz and B. Çiğdem B, "Epilepsi Hastalarında Levetirasetam Tedavisinin Otonom Sinir Sistemi Fonksiyonları Üzerine Etkileri," Epilepsi, vol. 26, no. 2, pp. 81-87, 2020.
[54] K. L. Chong, D. Holden and T. Olin, "Heart Rate Monitor," 2010. [Online]. Available: http://www.academia.edu/7884606/Heart_Rate_Monitor [Accessed: 24-June-2021].
[55] G. Aydın and O. Özhan, "Pulse Oksimetre Tasarım Ve Analizinin Yapılması", Proc. - 2. Ulusal Biyomedikal Cihaz Tasarımı ve Üretimi Sempozyumu, pp. 46-48, 2017.