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Effect of Muscle Fatigue on EMG Signal and Maximum Heart Rate for Pre and Post Physical Activity

Arifah Putri Caesaria[1], Endro Yulianto[1], Sari Luthfiyah[1], Triwiyanto[1], and Achmad Rizal[2]

[1] Department of Medical Electronics Technology, Poltekkes Kemenkes Surabaya, Indonesia
[2] School of Electrical Engineering, Telkom University, Bandung, Indonesia

[#]**Corresponding author:** Endro Yulianto (email: endro76@poltekkesdepkes-sby.ac.id)

ABSTRACT Sport is a physical activity that can optimize body development through muscle movement. Physical activity without rest with strong and prolonged muscle contractions results in muscle fatigue. Muscle fatigue that occurs causes a decrease in the work efficiency of muscles. Therefore, current study was carried out aiming to detect the effect of muscle fatigue on cardiac signals by monitoring the Electrocardiography (ECG) and Electromyography (EMG) signals. ECG is a recording of the heart's electrical activity on the body's surface, while EMG is a technique for measuring electrical activity in muscles. This study integrated ECG and EMG signal-tapping tools to detect the effect of cardiac bioelectrical signals on muscle fatigue in respondents who exercise routinely, rarely, and very rarely. Furthermore, the research method used was the Maximum Heart Rate (MHR) with a research design of one group pre-test-post-test. The independent variable was the ECG signal when doing plank activities, while the dependent variable is the result of the ECG signal monitoring. In order to get the MHR results, respondents used the Karnoven formula and performed the T-test. Test results further showed a significant value (p-Value <0.05) in pre-exercise and post-exercise. When the respondent experienced muscle fatigue, it showed the effect of changes in the shape of the ECG signal which was marked by the presence of movement artifact noise. It was concluded that the tools in this study can be used properly. However, this study also has limitations including noise in the AD8232 module circuit and the display on telemetry where the width of the box cannot be adjusted according to the ECG paper. The results of this study were useful as a reference for someone to be more careful in doing high-intensity exercise so as not to have an impact on the risk of heart disease. It is recommended for further research to use components with better quality and replace the display using the Delphi interface.

INDEX TERMS Fatigue, ECG, Maximum Heart Rate, EMG

I. INTRODUCTION

Exercise is basically a physical activity that can help optimize body development through movements based on the muscle movement [1]. In the world of sports, achievement and fitness can be achieved not only with talent or nutrition but also with the right training program. Athletes need good physical fitness so they do not get tired quickly during exercise and strong and prolonged muscle contractions are produced.

Fatigue is defined as a decrease in the strength of an induced muscle contraction protocol. Muscle fatigue is a decrease in the ability to generate strength caused by exercise without rest. Abnormal fatigue can also be caused by restriction or interference with different stages of muscle contraction. Muscle fatigue that occurs will result in a decrease in the work efficiency of these muscles [2][3][4].

ECG (Electrocardiography) is a recording of the electrical activity produced by the heart on the surface of the body. This was originally observed by A. D. Waller in 1889 using his pet bulldog as the signal source and a capillary electrometer as the recording device. In 1903, W. Einthoven improved the technology by using a string galvanometer as a recording device and employing human subjects with various heart defects. To record an ECG waveform, a differential recording between two points on the body was made [5][6]. ECG can be used to record data on the electrical activity of the heart muscle, including Heart Rate Variability and the duration of the QRS signal. EMG and ECG may be a promising methods for detecting fatigue [7] because ECG has a high linear relationship with oxygen intake, is the most commonly used indicator, and can answer human physiological problems in static and dynamic conditions. The onset of fatigue can be determined by analyzing bio signals such as surface electromyography (sEMG) and electrocardiogram (ECG). Physiological parameters such as pressure and heart rate have also been used to estimate fatigue onset and recovery time [8][9]. ECG signal was used to categorize subjects into two groups, namely moderate fatigue and severe fatigue [10][11]. In fact, fatigue can be classified as central and peripheral fatigue; the former is associated with the central nervous system (CNS), while the latter is associated with the peripheral neuromuscular system [12]. The exertion scale rating (RPE) is considered a comfort index that is usually used to monitor subjective perceived intensity of exercise [13][14][15].

EMG is a technique for measuring the electrical activity of muscles. EMG signals are used to evaluate fatigue by monitoring changes in activity electrical signals generated by muscle fibers such as muscle weakness, numbness, certain types of pain, cramps, and muscle disorders such as polymyositis or biomechanics of living creatures. In addition, it can also be used to determine the level of weakness and muscle strength for recovery purposes [16][17][18].

Previous studies discussing fatigue detection with EMG and ECG parameters in patients during various physical activities have been widely studied, such as studies that developed the dynamics of heart rate with muscle activity, which used HRV and EMG signals in 32 subjects during isometric contraction to determine differences in people with and without muscle fatigue. The HRV feature that is used as the system input to determine the state of fatigue is characterized by analyzing the EMG signal during muscle contraction [19][20].

Fauzani. N Jamaluddin et al, studied muscle activity before and after a single treadmill test. In the study, fatigue mapping was carried out by using EMG and ECG parameters as well as heart rate as a physiological indicator. The two analyses were based on the time and frequency of the time chosen to process the signal. The results showed that the electromyography amplitude and heart rate returned to normal (healed) within two to three hours, and the average frequency indicated a faster recovery [21].

Xi Luo carried out a study to detect fatigue and abnormal events by using HRV extraction from ECG signals to further analyze the situation during an exercise. In this case, the exercise was where the peak of the R wave in the QRS complex of each heartbeat cycle is the point with the greatest amplitude and the representative point of each cycle and the time interval between 2 adjacent R wave crests. For example, RR interval is used as the time interval between two heartbeat cycles. HRV features in the frequency domain include low frequency power (LF), high frequency power (HF), total power (TP), and low frequency and high frequency power (LF/HF) ratio. LF refers to power in the 0.04Hz- 0.15Hz frequency band in the HRV power spectrum. Electrocardiograph (ECG) signals are collected from people's daily sports and exercise using smart wearable devices. Second, baseline drift, motion artifacts, power frequency interference, and EMG interference signals in the electrocardiograph (ECG) are eliminated by fast median filtering, normalized least squares filter (NLMS), Butterworth low-pass filter, and wavelet filter. Electrocardiograph (ECG) signals are sampled through a 20-second sliding window [22].

Jianmei Lei1, Fangli Liu and Qingwen further developed real-time driving fatigue detection and early warning which are very important to reduce the number of traffic accidents, injuries, and deaths with ECG parameters. The ECG signal used the HRV (Heart Rate Variability) time-frequency domain index to improve signal accuracy. In this study, in order to realize real-time fatigue state detection, we focused on short time period ECG signals. As previously mentioned, the LF (Low Frequency) and HF (High Frequency) temperature-insensitive ECG indices cover the frequency bands of 0.04 0.15Hz and 0.15-0.4Hz, respectively [23].

In 2015, Wen Chen conducted research to monitor and analyze muscle fatigue and cardiac stress on stationary bicycle. In the study, when cycling was initiated, the wearable wireless sensor synchronously collected EMG and ECG data from the subject and then sent it to an A/D converter so that the system PC could acquire digital data for on-line monitoring and analysis during exercise. The system PC was used to perform online analysis that was carried out through several steps. The first step is acquiring and displaying ECG, EMG, HR, and cycle speed data. The second step is preprocessing the collected raw ECG and EMG data. The third step is conducting Fast Fourier transform (FFT) based power spectrum computing the DFA scaling exponent. The last step is converting all numerical results into fatigue and cardiac stress-related parameters (e.g., FPM and CSI) which are used for monitoring and analysis of cardiac fatigue and stress [24].

Furthermore, Alberto conducted a study in 2019 on the use of alternative non-invasive methodology for muscle fatigue detection relying on the analysis of two Autonomous Nervous System (ANS) correlates, i.e., the electrodermal activity (EDA) and heart rate variability (HRV) series. In the study, positioned patients were asked to perform two isometric force production tasks with their right arm: maximum voluntary isometric contraction (MVC) and sub maximal exhausting contraction. Each subject was seated in a comfortable chair, with elbows fully extended along the body, and straps attached to wrists and connected to load cells (i.e., dynamometers)[25].

In 2021, Elsa Puspa Nikmatuzaroh, Rachmad Setiawan, and Nada Fitrieyatul Hikmah conducted research to detect muscle fatigue in drivers using fuzzy logic method. In this study, the aim was to detect fatigue when the respondent was in a driving position or driving with EMG, ECG and Oxygen Saturation parameters. This study used the Fast Fourier Transform (FFT) to determine the amplitude of the response [26].

In addition, Fu RongRong also conducted research in 2013 to detect fatigue while driving using non–contact ECG and EMG signal measurement system. In this study, the aim was to find features of physiological signals that are of corresponding change with the loss of attention caused by driver fatigue [14].

Based on the research that has been done, there are several things that need to be improved, namely developing and integrating ECG and EMG tools to see the effect of muscle fatigue resulting from physical activity on ECG signals. If in previous studies HRV was widely used as a parameter of ECG to detect muscle fatigue, then in this study, the Maximum Heart Rate parameter was used from 3 categories of respondents, namely often, rarely, and very rarely exercise. In this case, respondents were measured before and after carrying out muscle contraction movements by doing planks.

The contribution of this study was to provide a reference for someone who does physical activity in the form of strenuous exercise that muscle fatigue resulting from excessive exercise, especially for someone who rarely exercises can increase heart rate quickly.

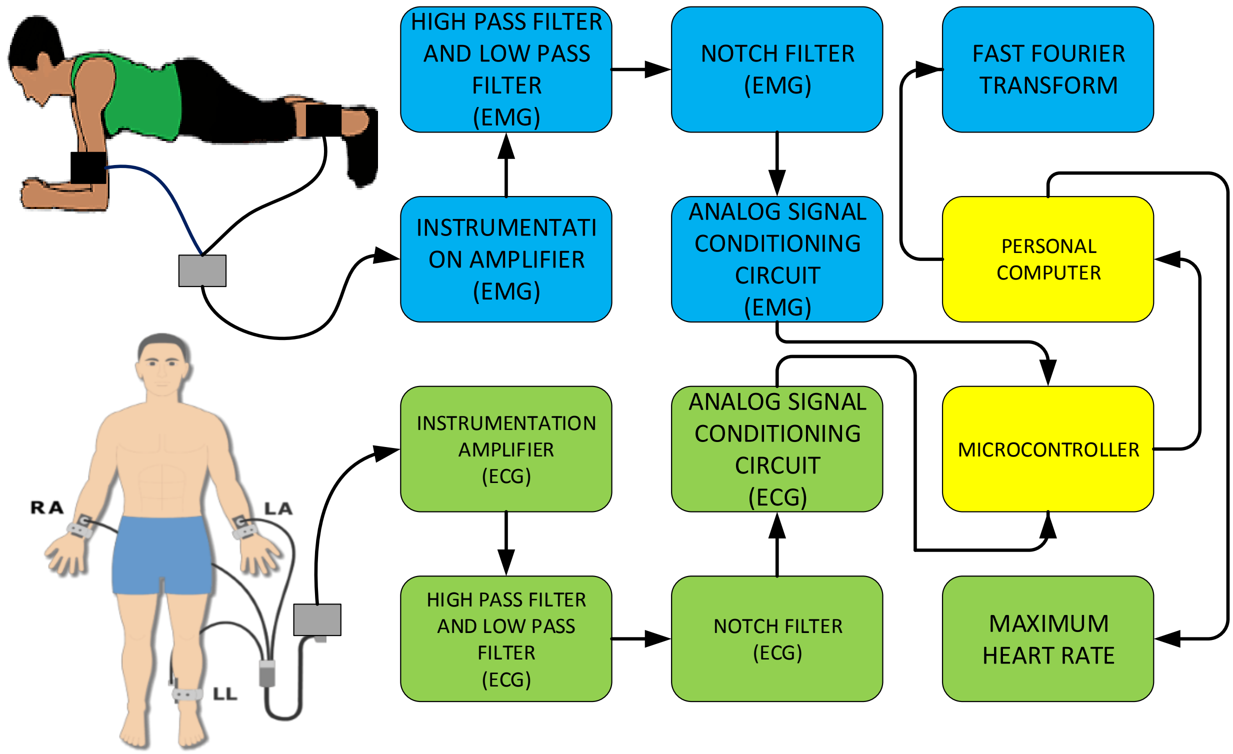

FIGURE 1 Data acquisition system and block diagram

II. MATERIALS AND METHODS

A. EXPERIMENTAL SETUP

This study used 10 formal respondents with several inclusion criteria, including at the age of 18 – 23 years old, do not smoke, are male, as well as have body weight of 60 – 70 kg, 70 – 80 kg and 80 – 90 kg. Furthermore, the frequency of exercise activity of the respondents was grouped into Often, Rarely, and Very Rarely.

ECG and EMG signals from respondents were measured before and after doing the plank movement. Each respondent performed the plank movement 5 times with 5-minute intervals. Each plank movement was performed at different time intervals according to the muscle strength of each respondent.

B. MATERIALS AND TOOL

This study used disposable ECG electrodes (OneMed, Jayamas Medical Industri, Indonesia). The electrodes were placed on the upper and left chest surfaces of the respondents. Furthermore, AD – 8232 module, Notch Filter, Adder and Non – Inverting circuit. Arduino Mega microcontroller were used for ECG data acquisition and communication to computer units using Telemetry Viewer, LCD I2C was used as BPM display, ECG cable, and digital storage oscilloscope (Textronic, DPO2012, Taiwan) was used to test analog circuits. Furthermore, a phantom ECG (Fluke, PS320, USA) was used to calibrate the analog circuit.

C. THE DIAGRAM BLOCK

In this study, a data acquisition system was created for tapping ECG and EMG signals as shown in FIGURE 1 and described in detail in the block diagram. The electrodes will tap the heart signal to be attached to the Left Arm/LA, Right Arm/RA, and Left Leg/LL. The result of the intercepted signal was then amplified and filtered analogously using a series of High Pass

Filters, Low Pass Filters, Notch Filters, and the buffer circuit so that the detected signal was the actual signal. The results of the ECG signal was then processed by the Arduino Uno microcontroller block working with C programming language to process data and display the results of the ECG signal and transfer it to a PC/Laptop device. PC/Laptop functions to receive and process data, which then the results are displayed in the form of an ECG signal construction. Based on the data obtained, the Maximum Heart Rate value was obtained.

D. THE FLOWCHART

FIGURE 2 shows the flow chart of the processing. When the device was turned on, the user attached electrodes to the patient for tapping the heart signal. After the tool was turned on, it initialized and obtained ADC data from the ECG instrumentation leads which read muscle signals. Furthermore, the signals were processed on the microcontroller and sent to the PC so that it can be monitored.

E. DATA ANALYSIS

Maximum Heart Rate (MHR) is commonly used to estimate exercise intensity by the Karvonen formula, and there are several methods for calculating it. In this study, we used pedaling experiments on a cycle ergometer to evaluate the method of determining the MHR to select the most suitable one for the Karvonen formula. The Karvonen formula is a general measure of exercise intensity. This is given by [27].

$$\frac{HR-HR_r}{HR_{max}-HR_r}\ x\ 100\% \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

where HR is the measured heart rate, HRmax is the maximum heart rate, HRr is the resting heart rate, and %HRR is the heart rate reserve, which is used to determine exercise intensity. This is why the Karvonen formula is widely used in the field of rehabilitation and physical training. One of the variables in Karvonen's formula, (1), is HRmax, which is the heart rate a person has when he pushes his body to its limit. but also impose a heavy physical burden on the subject, as a convenience, one way to calculate it is based on the age of the subject [28]. A t - test is a type of statistical test that is used to compare the means of two groups. It is one of the most widely used statistical hypothesis tests in pain studies.

There are two types of statistical inference: parametric and nonparametric methods. Parametric method refers to a statistical technique in which one defines the probability distribution of probability variables and makes inferences about the parameters of the distribution. T tests can be divided into two types. There is the independent t test, which can be used when the two groups under comparison are independent of each other, and the paired t test, which can be used when the two groups under comparison are dependent on each other. T tests are usually used in cases where the experimental subjects are divided into two independent groups, with one group treated with A and the other group treated with B [29]. The author of this research used the t-test to determine changes in heart-rate values during pre-exercise and post-exercise. The test results showed a significant change in value (p-value<0.05) in the pre-exercise and post-exercise results.

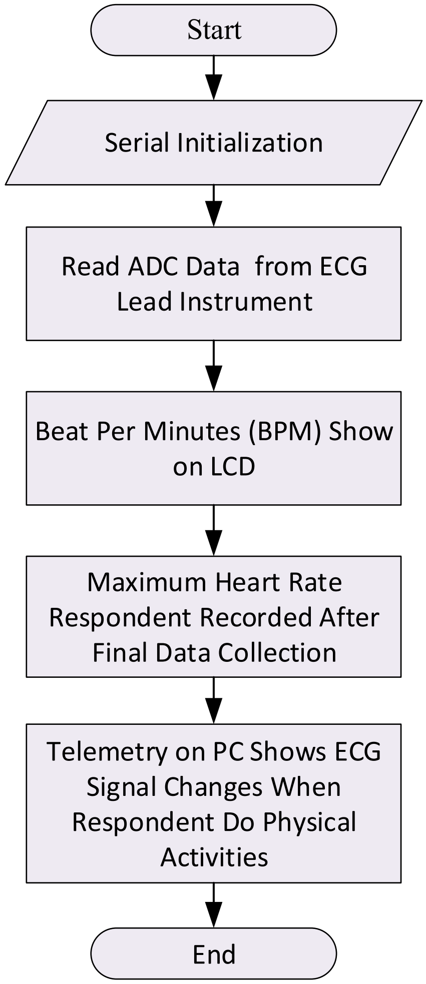

FIGURE 2 The Flowchart of ECG Monitor

III. RESULT

In this section, research results will be displayed consisting of the ECG Lead 2 signal tapping device, the ECG signal lead results in the Lead 2 position from respondents, and the Maximum Heart Rate average value of 10 respondents before and after doing planks. Before the ECG signal-tapping device was used to collect data on respondents, it is necessary to ensure that the tapping device is functioning properly. Therefore, in this study a Fluke MPS450 brand ECG Simulator or Phantom was used to simulate or generate ECG signals from the frontal (Lead I, II and III) and transverse (Chest 1 – 6) planes that are standardized. The tapping device that has successfully displayed the ECG signal from the Lead 2 position from the ECG Simulator correctly and without noise was then used to retrieve the lead ECG data from the respondent. The results of tapping the EMG signal before and after doing the plank for different durations according to the muscle strength of each respondent resulted in an increase in the MHR value which varied according to the frequency of activities the respondent had undertaken. The proposed design is shown in FIGURE 3.

FIGURE 3. The result of the ECG and EMG design

A. ECG DESIGN

In the analog part, there are Notch Filter, Adder Circuit, and Pre-Amplifier which consists of 3 TL 082 (OP-AMP). There are also several variable resistors (10k multiturn) for gain and offset adjustments. Meanwhile, the digital part consists of the Arduino Mega microcontroller which is the main board of the device as shown in FIGURE 4.

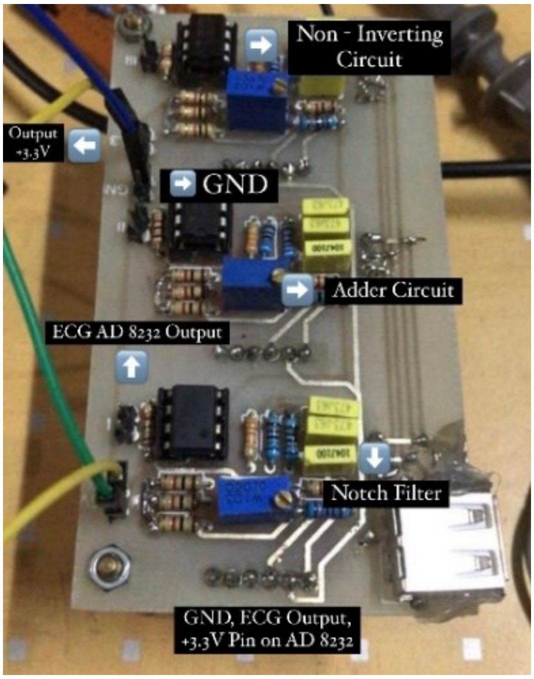

FIGURE 4. The ECG design

B. ECG SIGNAL RESPONDENTS

In this study, ECG was also tested using the human body by attaching the four electrodes to RA, LA, RL and LL. The following is the ECG signal during plank exercise.

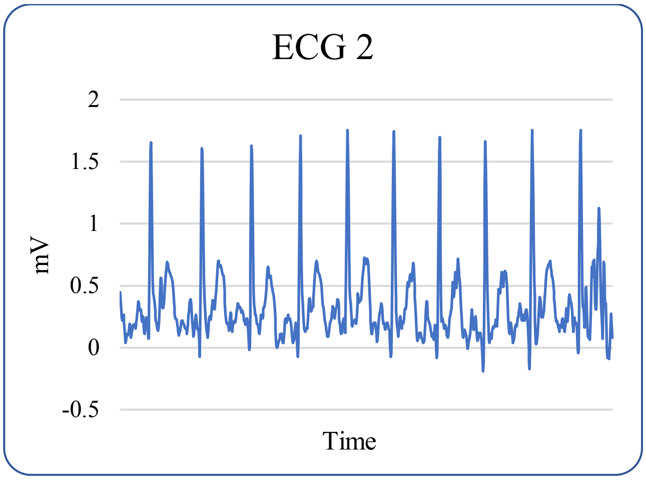

FIGURE 5. Graph of ECG Lead 2 during Plank exercise

FIGURE 5 is a graph plotting the Heart Rate value in respondent 1 to respondent 10 where it can be seen the difference in the Heart Rate value before – exercise with the heart rate value after – exercise from the 1st data to the 988th data when the respondent is pre-exercise with an amplitude of 1 – 1.5 mV. Data collection was carried out ten times with 5 repetitions and 2 stages of data collection, namely at pre-exercise and post-exercise. During the pre-exercise, the respondent first cleaned the body part that would be used. Next, the electrodes were installed to collect data using the telemetry viewer application and then plot the graph using excel. FIGURE 6 is a graph plotting the Heart Rate value in respondent 1 to respondent 10 where it can be seen the difference in the Heart Rate value before exercise with the heart rate value after the exercise. Table 1 shows the results of data collection on 10 respondents based on the average MHR value of the ECG signal that was tapped before and after carrying out the plank

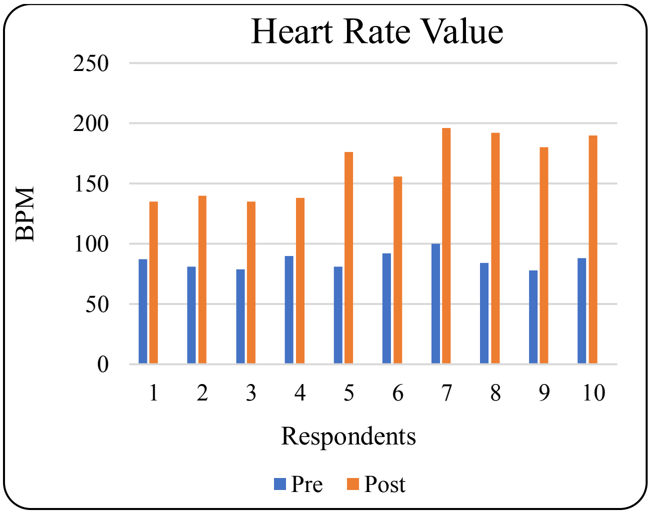

FIGURE 6. Graph of ECG Lead 2 during Post Exercise

TABLE 1
Heart Rate Data Responden 1 – 10

Subject	Weight (Kg)	Age (Years Old)	Exercise Frequency	Pre Exercise Mean ±SD (BPM)	Post Exercise Mean ±SD (BPM)	Plank Duration (Seconds)
1	60	22 ± 198	Rarely	87 ± 0.8232373	135 ± 25.0998	1:38
2	65	21 ± 199	Very Rarely	80 ± 5.357238	140 ± 15.96872	1:20
3	82	21 ± 199	Infrequently	79 ± .906519	160 ± 28.06243	1:2
4	68	23 ±197	Often	90 ± 10.6066	138 ± 20.12461	2:40
5	70	19 ± 201	Infrequently	81 ± 8.215838	176 ± 16.43168	1:8
6	60	22 ± 198	Infrequently	87 ± 0.823273	160 ± 6.5183501	1:24
7	81	21 ± 199	Very Rare	100 ± 97677	196 ± 22.64116	0:52
8.	81	21 ± 199	Very Rare	100 ± 712697677	196 ± 22.64116	0:52
9	70	22 ±198	Very Rare	76 ± 1.159502	180 ± 16.44553	1:35
10	84	22 ± 198	Very Rare	88 ±1.135292424	184 ± 15.47758	0:44

Table 2 shows the results of the parametric statistical test T-test to test the significance and relevance of MHR values from ECG signal data.

TABLE 2
Heart Rate T – Test Result

Variable	Pre – test	Post – test
Mean	85.2	166.1
Variance	47.288	520.988
Observations	10	10
Pearson Correlation	0.186	-
Df	9	-
T Stat	-11.332	-
P(T<=T) One – Tail	6.261E-07	-
T Critical One – Tail	1.833	-
P(Y<T) Two Tail	1.252E-06	-

V. DISCUSSION

Based on the ECG output measurements, the signal generated when using the input of the ECG simulator shows the correct ECG signal pattern consisting of P, Q, R, S, and T waveforms with 1 mV amplitude, for various BPM (30, 60, 120, 180 and 240), and a sensitivity of 1mV. The ECG value was read by the AD – 8232 modules. Pin A0 is the input for recording Lead 1, while Pin A1 is the input for recording Lead 2. Furthermore, Lead A2 is the input for recording Lead 3. Then the ADC data were processed by the Arduino Mega microcontroller. Then, the recording of ECG signal was conducted using the telemetry viewer application which was connected to the Arduino Mega using serial communication. After recording the ECG signal, it will be stored in CSV format and the data were converted into txt format.

In Table 1, respondent-7 with a body weight of 83 kg, aged 21 years, and has very rare exercise frequency obtained pre-exercise heart rate values of 100 and post-exercise value of 196. This occurred because when approaching the Maximum Heart Rate value, they have reached fatigue. In the 4th respondent with a body weight of 68 kg, aged 23 years old, and has frequently exercise, the heart rate in the pre-exercise was 90, while during the post-exercise was 130. So, it had no effect on the Maximum Heart Rate value not reaching fatigue. Factors that affect the low heart-rate value in respondent-4 include the frequency of exercise and body weight. Respondent-4 with the frequency of exercise often shows that the post-exercise heart rate has no effect on the Maximum Heart Rate. Factors that affect the high heart-rate value in respondent-7 include the frequency of exercise and body weight. Respondent-7 with the frequency of exercise very rarely shows that the heart rate has an effect on the Maximum Heart Rate.

The author used the t-test to determine changes in heart-rate values during pre-exercise and post-exercise. The test results showed a significant change in value (p-value <0.05) in the results of pre-exercise and post-exercise. This research has advantages over previous studies, including combining 2 medical devices, namely ECG and EMG. Where both tools can show the effect of muscle fatigue on heart signals by using data from increasing the respondent's Heart Rate value in pre-exercise and post-exercise.

V. CONCLUSION

This study aims to detect the effect of muscle fatigue on cardiac signals on physical activity by monitoring EMG and ECG signals (ECG Parameters). It may be concluded that the system can be utilized to detect fatigue using ECG and EMG monitoring. In testing using the T-test on pre-exercise and post-exercise, there was a significant change in value (p-Value <0.05) in Maximum Heart Rate. The results of Maximum Heart Rate data on respondents by showing the average value of pre-exercise respondents of 85.36 + SD of 6.736171019, on post-exercise an average of 163.6 + SD of 24.84708791. When the respondent experiences muscle fatigue, it shows a change in the form of the ECG signal in the form of noise artifact movement. Respondents who often exercise regularly, while doing planks until they reach fatigue, show a heart rate value of 160 bpm and a Maximum Heart Rate value of 199 bpm. Meanwhile, respondents whose exercise frequency is very rare, when doing planks until they reach fatigue, show a heart rate of 196 bpm which is close to the Maximum Heart Rate value of 199 bpm. Respondents with very rare exercise frequency feel tired faster than respondents who exercise regularly.

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