Lampiran 1 Contoh *Informed Consent*

SURAT PERSETUJUAN SETELAH PENJELASAN

(INFORMED CONSENT)

Saya yang bertanda tangan dibawah ini:

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Setelah mendapatkan penjelasan terkait fakta-fakta, resiko, dan manfaat penelitian, saya menyatakan bersedia terlibat sebagai subjek penelitian tentang “Pemanfaatan Sinyal Emg Menggunakan Bitalino untuk Pasien *Post-stroke* Dalam Mengukur Kekuatan Otot *Flexor Carpi Radialis*”. Apabila sewaktu-waktu saya mengundurkan diri dari penelitian, maka kepada saya tidak ada tuntutan apapun.

Demikian surat persetujuan kebersediaan terlibat dalam penelitian ini dibuat untuk dapat digunakan seperlunya.

Surakarta, ………………
memberi pernyataan

(………………………)

Lampiran 2 Signal Pre-processing dengan Matlab

```
%RAW SIGNAL

%Subjek 1 Post-stroke
%jsr = JokoSanRAW;
%Plot Raw Signal
%plot(jsr)
%title('EMG Raw Data')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([470 530])

%Subjek 2 Post-stroke
%sr = SlametRaw;
%Plot Raw Signal
%plot(sr)
%title('EMG Raw Data')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([470 530])

%Subjek 3 Post-stroke
%x = PostStrokeSubjek3Raw_ROI;
%Plot Raw Signal
%plot(x)
%title('EMG Raw Data')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([470 530])

%Subjek 4 Normal Individuals
%dr = DihartoRAW;
%Plot Raw Signal
%plot(dr)
%title('EMG Raw Data')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([250 850])
```

```
%Subjek 5 Normal Individuals
%syr = SuyantoRAW;
%Plot Raw Signal
%plot(syr)
%title('EMG Raw Data')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([390 660])

%Subjek 6 Normal Individuals
%tr = TugiRAW;
%Plot Raw Signal
%plot(tr)
%title('EMG Raw Data')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([390 660])

%BANDPASS FILTER

%Subjek 1 Post-stroke
%jsbp = JokoSanBP;
%Plot Bandpass Filtered Signal
%plot(jsbp)
%title('EMG Signal Band Pass Filter Applied')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([-20 20])

%Subjek 2 Post-stroke
%sbp = SlametBP;
%Plot Bandpass Filtered Signal
%plot(sbp)
%title('EMG Signal Band Pass Filter Applied')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([-20 20])

%Subjek 3 Post-stroke
%y = PostStreokeSubjek3Smooth_ROI;
%Plot Bandpass Filtered Signal
%plot(y)
```

```
%title('EMG Signal Band Pass Filter Applied')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([-20 20])

%Subjek 4 Normal Individuals
%dbp = DihartoBP;
%Plot Bandpass Filtered Signal
%plot(dbp)
%title('EMG Signal Band Pass Filter Applied')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([-300 300])

%Subjek 5 Normal Individuals
%sybp = SuyantoBP;
%Plot Bandpass Filtered Signal
%plot(sybp)
%title('EMG Signal Band Pass Filter Applied')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([-100 150])

%Subjek 6 Normal Individuals
%tbp = TugiBP;
%Plot Bandpass Filtered Signal
%plot(tbp)
%title('EMG Signal Band Pass Filter Applied')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([-100 150])

%Normalisasi
%Subjek 1 Post-stroke
%njsbp = sbp/max(abs(jsbp));
%plot(njsbp)

%Subjek 2 Post-stroke
%nsbp = sbp/max(abs(sbp));
%plot(nsbp)

%Subjek 3 Post-stroke
```

```
%nx = y/max(abs(y));
%plot(nx)

%Subjek 4 Normal Individuals
%ndbp = dbp/max(abs(dbp));
%plot(ndbp)

%Subjek 5 Normal Individuals
%nsybp = sybp/max(abs(sybp));
%plot(sybp)

%Subjek 6 Normal Individuals
%nsybp = tbp/max(abs(tbp));
%plot(tbp)

%Rectification

%Subjek 1 Post-stroke
%jsrf = abs(jsbp);
%plot (jsrf)
%title('EMG Signal Rectified')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([0 30])

%Subjek 2 Post-stroke
%srf = abs(VarName6_ROI);
%plot (srf)
%title('EMG Signal Rectified')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([0 30])

%Subjek 3 Post-stroke
%rx = abs(y);
%plot (rx)
%title('EMG Signal Rectified')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([0 30])

%Subjek 4 Normal Individuals
%drf = abs(dbp);
```



```
%plot (drf)
%title('EMG Signal Rectified')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([0 200])

%Subjek 5 Normal Individuals
%syrf = abs(sybp);
%plot (syrf)
%title('EMG Signal Rectified')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([0 200])

%Subjek 6 Normal Individuals
%trf = abs(tbp);
%plot (trf)
%title('EMG Signal Rectified')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([0 200])

%Savitz Golay Smoothing
%plot(rx,'DisplayName','rx');hold
on;plot(rx_ROI,'DisplayName','rx_ROI');hold off;
%title('EMG Signal Smoothed')
%xlabel('Time (second)')
%xlim([0 2000])
%ylabel('EMG Signal (Micro volt)')
%ylim([0 30])
```


Lampiran 3 Signal Extraction dengan Matlab

```
%Feature Extraction Time Domain
%IEMG
%IEMG1PS = sum(abs(JokoSanSmooth));
%IEMG2PS = sum(abs(SlametSmooth));
%IEMG3PS = sum(abs(rx_ROI));
%IEMG4NI = sum(abs(DihartoSmooth));
%IEMG5NI = sum(abs(SuyantoSmooth));
%IEMG6NI = sum(abs(TugiSmooth));
%MAV
%MAV1PS = mean(abs(JokoSanSmooth));
%MAV2PS = mean(abs(SlametSmooth));
%MAV3PS = mean(abs(rx_ROI));
%MAV4NI = mean(abs(DihartoSmooth));
%MAV5NI = mean(abs(SuyantoSmooth));
%MAV6NI = mean(abs(TugiSmooth));
%SSI
%SSI1PS = sum(JokoSanSmooth .^ 2);
%SSI2PS = sum(SlametSmooth .^ 2);
%SSI3PS = sum(rx_ROI .^ 2);
%SSI4NI = sum(DihartoSmooth .^ 2);
%SSI5NI = sum(SuyantoSmooth .^ 2);
%SSI6NI = sum(TugiSmooth .^ 2);
%VAR
%N1PS   = length(JokoSanSmooth);
%VAR1PS = (1 / (N1PS - 1)) * sum(JokoSanSmooth .^
2);
%N2PS   = length(SlametSmooth);
%VAR2PS = (1 / (N2PS - 1)) * sum(SlametSmooth .^
2);
%N3PS   = length(rx_ROI);
%VAR3PS = (1 / (N3PS - 1)) * sum(rx_ROI .^ 2);
%N4NI   = length(DihartoSmooth);
%VAR4NI = (1 / (N4NI - 1)) * sum(DihartoSmooth .^
2);
%N5NI   = length(SuyantoSmooth);
%VAR5NI = (1 / (N5NI - 1)) * sum(SuyantoSmooth .^
2);
%N6NI   = length(TugiSmooth);
%VAR6NI = (1 / (N6NI - 1)) * sum(TugiSmooth .^ 2);
%RMS
%RMS1PS = sqrt(mean(JokoSanSmooth .^ 2));
%RMS2PS = sqrt(mean(SlametSmooth .^ 2));
%RMS3PS = sqrt(mean(rx_ROI .^ 2));
%RMS4NI = sqrt(mean(DihartoSmooth .^ 2));
```

```
%RMS5NI = sqrt(mean(SuyantoSmooth .^ 2));
%RMS6NI = sqrt(mean(TugiSmooth .^ 2));
%WL
N1PS  = length(JokoSanSmooth);
WL1PS = 0;
for k = 2:N2PS
  WL1PS = WL1PS + abs(JokoSanSmooth(k) -
JokoSanSmooth(k-1));
end
N2PS  = length(SlametSmooth);
WL2PS = 0;
for k = 2:N2PS
  WL2PS = WL2PS + abs(SlametSmooth(k) -
SlametSmooth(k-1));
end
N3PS  = length(rx_ROI);
WL3PS = 0;
for k = 2:N3PS
  WL3PS = WL3PS + abs(rx_ROI(k) - rx_ROI(k-1));
end
N4NI  = length(DihartoSmooth);
WL4NI = 0;
for k = 2:N4NI
  WL4NI = WL4NI + abs(DihartoSmooth(k) -
DihartoSmooth(k-1));
end
N5NI  = length(SuyantoSmooth);
WL5NI = 0;
for k = 2:N5NI
  WL5NI = WL5NI + abs(SuyantoSmooth(k) -
SuyantoSmooth(k-1));
end
N6NI  = length(TugiSmooth);
WL6NI = 0;
for k = 2:N6NI
  WL6NI = WL6NI + abs(TugiSmooth(k) -
TugiSmooth(k-1));
end

%Feature Extraction Frequency Domain
%MDF
%MDF1PS = medfreq(JokoSanSmooth);
%MDF2PS = medfreq(SlametSmooth);
%MDF3PS = medfreq(rx_ROI);
%MDF4NI = medfreq(DihartoSmooth);
```



```
%MDF5NI = medfreq(SuyantoSmooth);
%MDF6NI = medfreq(TugiSmooth);
%MNF
%MNF1PS = meanfreq(JokoSanSmooth);
%MNF2PS = meanfreq(SlametSmooth);
%MNF3PS = meanfreq(rx_ROI);
%MNF4NI = meanfreq(DihartoSmooth);
%MNF5NI = meanfreq(SuyantoSmooth);
%MNF6NI = meanfreq(TugiSmooth);
```

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Lampiran 11 Publikasi

Utilization of EMG Signals Using Bitalino for *Post-stroke* Patients in Mapping Characteristics of Flexor Carpi Radialis Muscle

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Abstract

EMG signal strength measured using Bitalino on the flexor carpi radialis muscle showed that post-stroke patients has lower EMG signal strength levels than normal individuals. The time domain extraction feature provides information on the average strength of the flexor carpi radialis muscle EMG signal in post-stroke patients as follows, IEMG of 8,678 µV, MAV of 4,338 µV, SSI of 16,465 µV, VAR of 82,327 µV, RMS of 8,515 µV, WL of 592,203 µV. The frequency domain extraction features include MNF of 0.064 µV and MDF of 0.027 µV. A stronger grip strength tends to produce a more significant EMG signal. This study provides a mapping of a large gap between the EMG signal strength of post-stroke patients and normal individuals that can be used as a reference for therapists in providing rehabilitation for post-stroke patients. EMG signals store important information regarding muscle condition, so signal recording and processing are crucial. This study utilizes Bitalino, which records EMG activity in muscles reliably and precisely. Matlab *software* is very reliable used for filtering, rectification, and smoothing. Bandpass filters with cut-off frequencies below 30 Hz and above 600 Hz are used. Smoothing uses Savitz-Golay statistics to obtain a more precise signal.

Keywords
EMG, Flexor Carpi Radialis, Bitalino, Matlab, Post-stroke

1. Introduction

A stroke is a condition of a person who experiences disturbances in moving the body. A stroke occurs when brain cells die due to obstruction of blood flow to the brain. Blocked blood flow due to damage or blockage of blood vessels. Stroke patients find it difficult to do daily activities. Stroke patients can experience death or disability. Stroke leading disability and death in the elderly (Hussain and Park 2021). Stroke impacts decreased neurological function for millions of people, causes physical disability and dependent lives, and increases the risk of psychological disorders that lead to depression (Campbell et al. 2019). An unhealthy lifestyle is a major factor in stroke (Rahmatillah et al. 2018). Stroke patients become post-stroke after a particular time. Post-stroke patients are dependent on others to support daily life and incur high costs in care and rehabilitation.

Stroke patients are predicted to increase to 25-30 sufferers per mile in Indonesia, with a stroke disability rate of 65% (Rahmatillah et al. 2018) and an increasing number post-stroke. 50% of post-stroke patients have a unilateral motor deficit, which significantly reduces upper limb function (Franck et al. 2019). Functional damage to the limbs causes disability and decreases productivity (Karunia 2016). Post-stroke rehabilitation is urgently needed, along with the increasing number of sufferers and disabilities caused by stroke.

Conventional rehabilitation depends on the therapist's direction. It is assessed subjekively for post-stroke patients and requires a long time and high effort, affecting the patient's motivation to decrease (Cai et al. 2019). The therapist must be able to detect the post-stroke condition experienced by the patient to carry out rehabilitation appropriately. The condition of the muscles and nerves of post-stroke patients provides information in identifying the patient's condition. Muscle strength and Electromyography (EMG) can identify the condition of muscles.

Measurement of muscle strength identified through dynamometer and signal strength by Electromyography (EMG). The post-stroke patient pulls the dynamometer lever with all his strength three times in one hand after a stroke. The mean score was calculated using one-handed measurement. EMG is a biomedical signal obtained by detecting muscle activity. EMG signal is detected from muscle contraction (Desplenter et al. 2020). Normal muscle contraction produces certain tension and frequency (Nemes et al. 2021). EMG signal can be measured using various *tools* such as Myoarmband, Biometric, Shimmer, Biosemi, BTS Bioengineering, *Biosignalplux*, Bitalino, Delsys, etc. Bitalino and OpenSignals *software* are *tools* used to record and acquire EMG signals (Moital et al. 2015). Bitalino has a reliable signal recording feature for muscle evaluation, physical condition, and fitness (Toledo et al. 2020). Bitalino's empirical validation with Delsys and BioPack shows that Bitalino with low-cost technology provides similar results (Batista et al. 2019). Delsys costs around 15,000 £ whereas Bitalino only 150-200£ (del et al. 2019).

EMG signal record using Bitalino and the OpenSignals *software*. This signal is called a *Raw* signal. The *Raw* signal needs to be processed to obtain important information. Signals acquired from muscle activity were analyzed using MATLAB *software* for extraction (Sattar et al. 2019). Signal information is processed through signal pre-processing and extraction steps (Merletti and Cerone 2020). Signal pre-processing is carried out with the signal acquisition stage, then signal preparation through visualization, filtering, rectification, normalization, etc. Extraction steps processed signal using Time domain and frequency domain features. Pre-processing and extraction steps were processed using MATLAB *Software*.

This paper measures the EMG strength of flexor carpi radialis muscle using a dynamometer and Bitalino for mapping muscle conditions between normal individuals and post-stroke patients. This mapping is used as guidance and helps therapist defines post-stroke patient condition objectively.

2. Methods

2.1 Study Participants

Research approval obtained from the Health Research Ethics Committee (KEPK) Faculty of Medicine, Universitas Sebelas Maret (UNS). Six samples met the research criteria involved in the study by dividing three samples of post-stroke patients (treatment group) as PS and three samples of normal individuals (control group) as NI. Each subjek is willing to participate in the study, as evidenced by filling out and consenting to the informed consent. The characteristics of the research subjeks are determined by taking into account the factors that affect the strength of the EMG signal, such as age, weight, height, and circumferences based on inclusion criteria. BMI in the normal category with a value range of 18.5-25 kg/m2 (Eckel et al. 2018), has circumferences range of 16 – 26 cm (Arifi et al. 2019) on the maximum arm so that it can show the strength of the flexor carpi radialis muscle, normal individual age and post-stroke patients 50-65 years. The age-related loss of muscle mass, strength, and physical function, largely accounts for physical frailty (Yoshimura et al. 2019). The specific range of age and an equal number of subjeks selected to reduce the standard deviation. Characteristics of participants show in TABLE 1. The exclusion criteria included post-stroke patients with no tremor, spastic, or residue. Subjek recruitment and retention can be seen in FIGURE 1.

Table 1. Characteristics of Participants

Subjek	Name	Gender	BMI (Kg/m^2)	Age (Years)	Circumferences (Cm)
Post-stroke	Subjek 1 (A1)	Male	24,14	63	23
	Subjek 2 (A2)	Male	24,29	63	25
	Subjek 3 (A3)	Male	21,05	64	23,5
Normal Individuals	Subjek 1 (B1)	Male	23,22	50	24
	Subjek 2 (B2)	Male	22,98	64	26
	Subjek 3 (B3)	Male	23,56	65	26

2.2 Electronic Hand Dynamometer

The Electronic Hand Dynamometer EH101 is an instrument for measuring hand grip strength to track improvements in strength during rehabilitation. Test grip strength in a fast, simple, and safe way to get objective measurements. Has specifications, namely: units in Kg or lb, max capacity 90 Kg/198 lb, scale accuracy 0.1 Kg/ 0.2 lb, power supply 2 x 1.5V AAA, tolerance 0.5 Kg/1 lb.

2.3 Bitalino

The Bitalino(r)evolution kit is an all-in-one board with all the blocks that can be connected with various sensors (ECG, EEG, EMG, Acc, etc.) and equipped with Bluetooth low energy (BLE) communication (Palumbo et al. 2021). The EMG sensor is specially designed for surface EMG. The bipolar configuration is ideal for low-noise data acquisition, and the *Raw* data output allows it for human-computer interaction and biomedical projects. Biosignalsplux is the latest wireless *toolkit* to collect and analyze reliable biosignal data (Palumbo et al. 2021). *Biosignalplux* offers a set of wired sensors and can be used with various biosignal sensors.

The Electromyography (EMG) sensor is a high-performance, low-noise bipolar sensor for muscle signal data acquisition. The sensors are designed to monitor muscle activity, and the bipolar configuration is ideal for data acquisition. *Raw* data output enables biomechanics and sports-related research with highly accurate signal capture results. Features include bipolar differential measurement, analog pre-conditioned, high signal-to-noise ratio, and medical grade *Raw* data output. This device is capable of showing and capturing signals in real-time. The EMG sensor has a single integrated channel with a triaxial accelerometer and magnetometer for real-time acquisition of muscle activity and motion data with the Bluetooth module. This sensor enables data acquisition at up to 16-bit resolution at *sampling rate*s up to 1000 Hz, with an internal battery providing sufficient power for continuous data streaming.

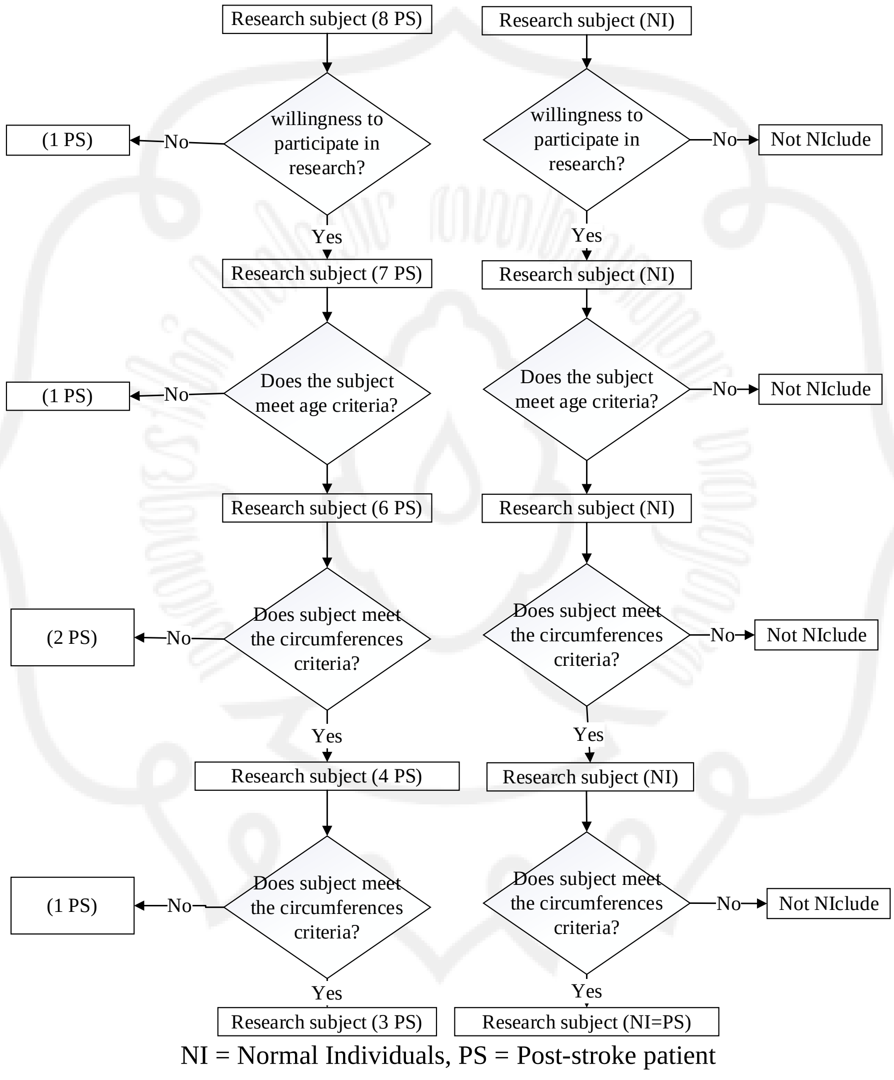


Figure 1. Flow diagram of subjek recruitment

2.4 Experiment Protocol

Measurement of grip strength with hand grip dynamometer to determine muscle strength in normal individuals and post-stroke patients. The test was carried out by considering the gender, BMI, circumferences, body position, and age of normal individuals and post-stroke patients. Set the gender on the dynamometer and the age of the subjek. Set up the dynamometer lever in the initial gripping position. The initial position of gripping show in Figure 2 (a). The initial position of the dynamometer lever for gripping is show in Figure 2 (b). Subjeks were asked to grip with all their strength in a sitting position. The position of the thumb holds the dynamometer, while the position index finger, middle finger, little finger, and ring finger hold the dynamometer lever. Subjeks were asked to do the power grip as strongly as possible. Record grip strength by normal and post-stroke individuals.

(a) (b)

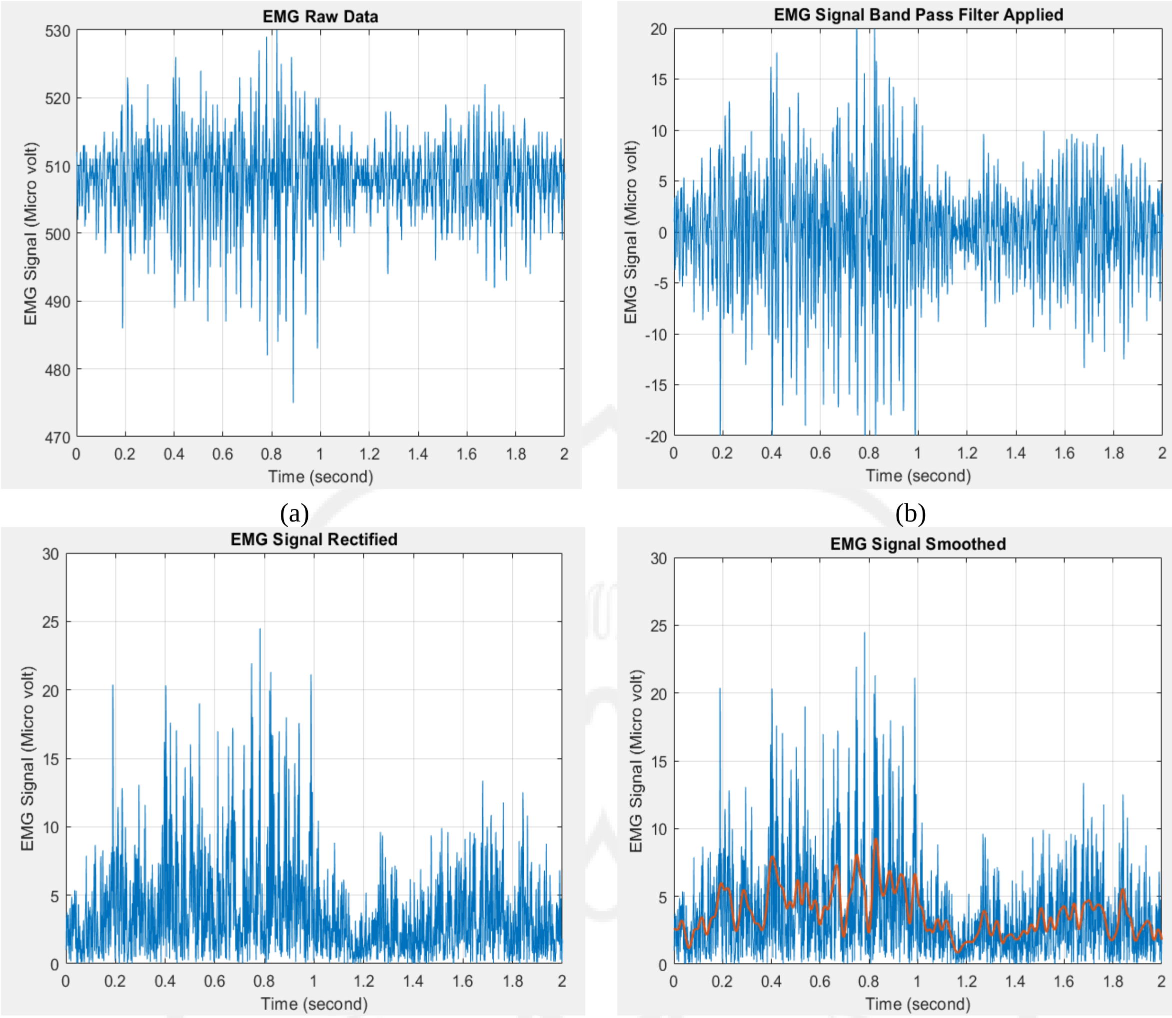
Figure 2. The initial position of gripping(a) and dynamometer lever (b)

The next measurement of muscle strength uses measurements based on EMG signals. The EMG signal was measured in the flexor carpi radialis muscle. Signal strength measurements were performed by targeting the flexor carpi radialis muscle of the forearm in an anterior position. The flexor carpi radialis muscle, located in the superficial layer, originates from the medial epicondyle of the humerus, runs obliquely to the side of the forearm, inserts at the base of the second and third metacarpal bones, and it is responsible for the movement of the index and middle fingers (Evelyn 2016). The electrode placement targeting flexor carpi radialis muscle show in FIGURE 3.

(a) (b)

Figure 3. Electrodes placement (a) kathode and anode (b) ground

EMG signal measurement is carried out with the subjek preparation stage, acquisition/recording of EMG signals with Bitalino *tools* and opensignals *software*, signal preprocessing including filtering, windowing, rectification, smoothing, and extracting EMG signals based on time domain and frequency domain. Signal preprocessing and extraction using MATLAB *software*. Filtering is the stage of suppressing unwanted components of the signal. The bandpass filter suppresses the signal at a frequency within the allowable range. This study uses a bandpass filter with a frequency range of 30 Hz-600 Hz. Signal windowing is viewing the signal in a certain time range from the entire signal. In this study has 6 subjeks with data recorded 30 second for each subjek. One cycle of gripping and relaxation movements or 2 second signal windowing performed on each subjek. The windowing technique show optimum range of overlap size from 10% to 30% of the length of a window size (Ashraf et al. 2021). Rectification is a step to turn all these negative values into positive ones, adding the values and making them integrative. Smoothing is finding important patterns in our data while leaving out unimportant things (i.e., noise) to get slow changes in value so that it is easier to see trends in our data. Sometimes when examining input data may need to smooth the data to see a trend in the signal.



(c) (d)

Figure 4. The signal processing

Then, for each post-stroke subjek and normal individual data, it goes through the signal processing stage, then the features are extracted. There are two types of signal extraction features: the time domain (measured as a function of time) and the frequency domain (measured using the signal spectrum). The following eight features, six features of time domains and two features of frequency domains are used in this paper show in TABLE 2. Extraction process carried using Matlab to identify the signal characteristic.

Table 2. Signal extraction features

Feature	Equation	Equation Number
Integrated EMG (IEMG)	$IEMG = \sum_{i=1}^{N} \lvert x_i \rvert$	(1)
Mean Absolute Value (MAV)	$MAV = \frac{1}{N} \sum_{i=1}^{N} \lvert x_i \rvert$	(2)
Simple Square Integral (SSI)	$SSI = \sum_{i=1}^{N-1} x_i^2$	(3)

Table 2. Signal extraction features (continue)

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Feature	Equation	Equation Number
Variance of EMG (VAR)	$VAR = \frac{1}{N-1}\sum_{i=1}^{N-1} x_i^2$	(4)
Root Mean Square (RMS)	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$	(5)
Waveform Length (WL)	$WL = \sum_{i=1}^{N-1} \lvert x_{i+1} - x_i \rvert$	(6)
Mean Frequency (MNF)	$MNF = \sum_{j=1}^{M} f_j P_j \Big/ \sum_{j=1}^{M} P_j$	(7)
Median Frequency (MDF)	$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j$	(8)

3. Results and Discussion

The purpose of this study is to obtain a mapping of the grip strength of post-stroke patients vs. normal individuals measured by a dynamometer and the grip strength of the flexor carpi radialis muscle as measured by electromyography using Bitalino. The measurement of grip strength using a dynamometer obtained that the grip strength of normal individuals vs. post-stroke patients. A comparison of grip strength between post-stroke patients and normal individuals Shows in FIGURE 5. Post-stroke patient grip strength is 3.1 kg for A1, 3.5 kg for A2, and 11.4 kg for A3, while normal individuals' grip strength is 34.7 kg for B1, 27.4 for B2, and 31.0 kg for B3. Normal individuals have much stronger than post-stroke patients.Signal processing starts from recording *Raw* EMG signals using Bitalino *tools* and OpenSignals *software*. *Raw* data is shows in FIGURE 4(a). This *Raw* signal barely collected from Bitalino recording. Furthermore, *Raw* signal filtering is carried out using the Matlab signal processing toolbox. Filter applied to eliminate or attenuate noise. The filtered *Raw* signal is shows in FIGURE 4(b). Then, rectification is carried out to obtain a signal in positive value because the EMG signal recorded through Bitalino has positive and negative values. EMG signals are rectified by lowering the baseline to zero and absolutizing the negative value. This is show in FIGURE 4(c). Rectified signal show has some rough shape that shows extreme signal peak and need to be smoothed. Smoothed signal show in FIGURE 4(d) by applying savitz-golay smoothing. All recorded signal from every subjek through this processing step before extraction process.

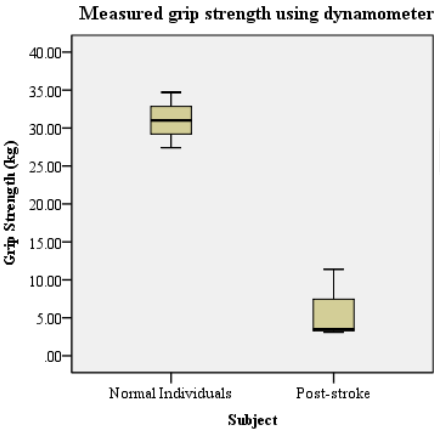

Figure 5. Measured grip strength using dynamometer between post-stroke patient and normal individuals

EMG signals recorded from post-stroke patients and normal individuals who have undergone signal processing were extracted using the feature time domain and frequency domain. TABLE 3 shows the extraction result.

Table 3. Time and frequency domain signal extraction result

		Time Domain						Frequency Domain	
Condition	**Subjek**	**IEMG**	**MAV**	**SSI**	**VAR**	**RMS**	**WL**	**MNF**	**MDF**
Post-stroke	A1	7,807	3,901	22,016	110,078	10,489	740,891	0,095	0,046
	A2	10,703	5,349	24,013	120,063	10,955	897,122	0,092	0,035
	A3	7,526	3,763	3,366	16,840	4,103	138,597	0,006	0,001
	Average	8,678	4,338	16,465	82,327	8,515	592,203	0,064	0,027
Normal Individuals	B1	111,537	55,741	748,777	3.743,884	61,172	2.841,575	0,009	0,001
	B2	42,646	21,312	123,432	617,163	24,837	2.574,390	0,032	0,001
	B3	104,281	52,115	716,893	3.584,465	59,855	2.859,188	0,010	0,001
	Average	86,155	43,056	529,701	2.648,504	48,621	2.758,384	0,017	0,001

*Extraction unit in micro volt

The time domain and frequency domain extraction features indicate the strength of the flexor carpi radialis muscle in gripping in post-stroke patients and normal individuals. The IEMG extraction feature shows the grip strength of the flexor carpi radialis muscle for post-stroke patients with an average EMG signal value of 8,678 µV with the strongest EMG signal strength not exceeding 10,703 µV. In contrast, the average EMG signal for normal individuals is 86,155 µV. Normal individual EMG signal strength is nine times stronger based on IEMG features. The same thing is shown by the MAV extraction feature, where the average grip strength of the flexor carpi radialis muscle in post-stroke patients with an average EMG signal of 4,338 µV, while for normal individuals, it is 43,056 µV, nine times stronger. Shifting to the SSI extraction feature, the flexor carpi radialis muscle hand strength for post-stroke patients with an average EMG signal of 16,465 µV and normal individuals of 529,701 µV. The strength of the normal individual EMG signal is thirty-two times more. In the VAR feature extraction, the EMG signal strength of normal individuals is 32 times stronger than that of post-stroke patients. The RMS and WL extraction features showed the same thing, the EMG signal strength of normal individuals was significantly stronger than that of post-stroke patients.
The frequency domain extraction feature shows something different: post-stroke patients have weak grip strength compared to normal individuals but have higher EMG signals. The EMG signal measured in the MNF extraction feature can be seen in post-stroke patients with an average of 0.064 µV, while normal individuals are 0.017 µV. Post-stroke patients have four times stronger EMG signals than normal individuals. The MDF extraction feature showed a more significant difference, where the EMG signal strength of post-stroke patients averaged 0.027 µV while normal individuals were 0.001 µV. Post-stroke patients had twenty-seven times stronger EMG signals.

4. Conclusion

This study shows the grip strength of post-stroke patients with normal individuals has a huge different, normal individuals tend to have a much stronger grip strength. Bitalino and Matlab can detect and process EMG signals reliably. The grip strength measured in the flexor carpi radialis muscle utilizing EMG signals showed that normal individuals tended to be stronger. The time domain feature extraction shows the strong EMG signal produced by the flexor carpi radialis muscle in normal individuals showing a stronger EMG signal than in post-stroke patients. However, feature extraction with the frequency domain shows the opposite, post-stroke patients tend to have stronger EMG signals than normal individuals.
Taking into account the results of grip strength measurements with a dynamometer and EMG, the subjeks with stronger grip strength had stronger EMG signals than normal individuals. In post-stroke patients, there are subjeks who have more grip strength but weaker EMG signals. This needs to be investigated further in future studies involving more post-stroke patients and more rigid inclusion criteria.

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