ELBOW ANGLE ESTIMATION FROM EMG SIGNALS BASED ON MONTE CARLO SIMULATION

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Graphical abstract

Abstract

Monte Carlo simulation is defined as statistical sampling techniques which is used to estimate the solutions of quantitative problems. The aim of this study is to develop Monte Carlo algorithm for elbow angle estimation from EMG signal as preliminary study for further research in rehabilitation tool to make a breakthrough rehabilitation tool for post-stroke patients based on muscle signals to carry out rehabilitation independently and consistently. The Monte Carlo simulation is performed to approach the model's angle from subject who takes 20 seconds lifting barbell repeatedly for 52 times. Monte Carlo simulations were carried out as many as 10,000 times because it was considered ideal testing for a model. In doing the estimation, the angle will be divided into four ranges, which are determined from the model's trend value, the estimation of the previous angle, the estimated error angle, and the previous measured angle. Then an average calculation is performed on the Monte Carlo simulation, which enters the angle range to determine the estimated value of the angle. The most optimal estimation is obtained from this study with RMSE (root mean square error) was 8.96°, and the correlation coefficient between estimate angle and the measured angle was 0.96.

Keywords: Muscle signal, elbow angle, estimation, Monte Carlo, EMG

1.0 INTRODUCTION

The cause of stroke disease is the disruption of the brain's blood circulation, which is affected by two significant grouped factors: unchangeable and changeable. Dinata *et al*. [1] stated that age and gender are examples of unchangeable factor, while the changeable factor could be hypertension, hyperglycemia, dyslipidemia, and job. In Asia, stroke is one of the deadliest diseases and the top cause of neuro disease, affecting mainly the upper extremities resulting in disability [2].

As a result, motoric rehabilitation is essential to improve the functionality of the upper extremities of the post-stroke patient. Purwanti and Maliya [3] explained that rehabilitation is a process to restore the physical condition as good as the condition before affected by the disease in a short period. Many tests and researches conducted and showed the improvement of the patient's condition with several rehabilitation techniques. For instance, intensive practice using an electromechanics device to help the patient's movement during lifting and walking, and the mental image procedure could be utilized as practice assistance because it activates many cortical neurons when the movement is initiated [4].

In general, the rehabilitation method in Indonesia is carried out with the assistance of physiotherapies manually. Following the movement line correctly, supervising movement pattern and supporting the disabled extremities are standard rehabilitation procedures [3]. According to Tao and Yu [5], good post-stroke rehabilitation is indicated by the continuous repetition and comparison between manual and exoskeleton therapies. Also, it is recommended to use exoskeleton therapy because it will enhance the rehabilitation quality based on the patient's experience and physiotherapies efficiency.

There are some physical practice therapy categories for rehabilitation: range of motion (ROM) exercise, resistance exercise, stretching, joint mobilization, aquatic exercise, and aerobic exercise [6]. Rhestifujiayani *et al.* [7] compared the rehabilitation method for post-stroke patients and found out that ROM exercise could strengthen post-stroke patients' muscle.

Paquin and Power's [8] research looked for the relation between muscle signal with torque and discovered that linear relation is the connection between both. He suggested pointing out the relation between muscle signal and angle to measure the joint's ROM. ROM itself is a movement that could be done of the typical joint [9].

Myers *et al.* [10] reported that EMG signal data must be preprocessed to ameliorate the EMG's surface or to see the best shape of the EMG signal (coherence) before the EMG is analyzed. The preprocessing of EMG signal consists of second-order Butterworth type IIR Band Pass Filter in the range of frequency 20 – 500 Hz, Butterworth type IIR Band Stop Filter 49 – 51 Hz, rectifier to get the positive value of the muscle signal, and smoothing. Meanwhile, the angle data only needs smoothing for the preprocessing. After preprocessing, the Probability Distribution Function (PDF) and Cumulative Distribution Function (CDF) will be seen to simulate estimation with the Monte Carlo method and estimate the angle from the muscle signal.

Doheny *et al* [11] conducted a study using the maximum voluntary contraction (MVC) method to estimate the elbow joint angle, but it did not have a significant effect on the force–EMG relationship of the biceps, as well as on Fmed was observed in the brachioradialis. Zhou *et al* [12] tried to apply the support vector machine (SVM) regression model to predict the position of the forearm. However, the RMSE value is still greater than the expected value, which is <15%, the RMSE obtained still reaches 19.07%, as well as the correlation coefficients obtained at 0.793 which are still far from 0.9. While Pang *et al.* [13] applying the Hill-Type-Based Muscular Model as the upper limb elbow joint representation, the results obtained are quite good with the correlation coefficient is above 0.97, but the highest RMSE obtained is still 19.35 +/- 3.15. Another study using auto-regressive integrated moving average with exogenous input (ARIMAX) [14] resulted in a fitness

value>0.9, but this method does not use feature extraction so it still uses 16 channels.

The Monte Carlo method is a method for estimating a statistic's sampling distribution that can be used to analyze statistical processes in a variety of ways. The following are some of the benefits of Monte Carlo simulation: measuring the robustness of parametric inference to violations of its assumptions, and comparing the qualities of two or more estimators using statistics with only a weak mathematical theory [15]. This method can be an alternative for elbow angle estimation from EMG signal.

This research aims to estimate or predict the elbow joint angle from the biceps brachii EMG signal as an input with the Monte Carlo method and use NI myDAQ for the data acquisition. The data of EMG signal is extracted by MyoWare Muscle Sensor, while the angle data of the elbow joint is collected by Rotary Encoder, which is an angle sensor. Both data are collected simultaneously for the input data, which subsequently will be processed to get the model resulting in simulating the estimation of the elbow's angle. The estimation results will be tested by comparing the Rotary Encoder sensor and goniometer output with the output of estimation. The testing is performed to know how good the estimation is.

2.0 METHODOLOGY

This study needs several steps before the Monte Carlo method is performed to estimate the elbow joint angle from the EMG signal. The first thing to do is collecting the EMG data from the biceps brachii muscle's subject as same as the angle data from the elbow joint's subject. Afterwards, preprocessing is conducted for both EMG signal and angle data. Third, the modelling with Curve Fitting (Nonlinear Regression) method is carried out. Lastly, the modelling will be simulated by the Monte Carlo method. Figure 1 shown the research flow diagrams.

2.1 Retrieval of EMG Signal and Angle Data

Both EMG signal and elbow's angle date are simultaneously recorded. Thus, the angle data will correspond with the EMG signal at the same time. Moving on to the subject, this research gathered the data 52 times from 22 years old and 65 kg subject with arm muscle area 47.2 cm2. In this research, the calculation of arm muscle area is based on the formula (1) [16]. Furthermore, the scheme of the data collection device could be observed in Figure 2.

$$MMA=(MAC-\pi(TSF)^2)/(4\pi) \qquad (1)$$
Where,
MMA = Midarm muscle area (cm2)
MAC = Midarm circumference (cm)
TSF = Triceps skinfold (cm)

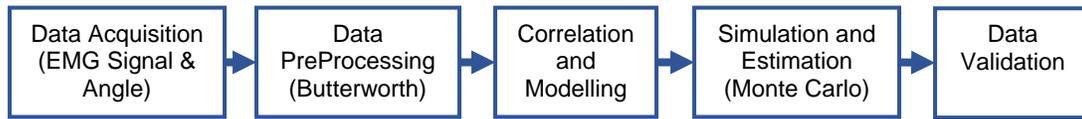**Figure 1** Research flow diagrams

Figure 2 The scheme of EMG signal and angle data collection

The subject uses an exoskeleton on his upper part of his right hand and is strapped on his lower part. Moreover, the exoskeleton is stuck with double tape. Hence, it will be firm and reduce the chance of generating notion motion artefact on EMG signal. The electrode is placed on the biceps brachii muscle in the centre of the muscle verging the elbow's tendon, while the ground of the electrode is attached to the elbow. MyoWare Muscle sensor is connected to NI myDAQ as data acquisition with the breadboard.

2.1.1 Validating Elbow's Angle

Before the acquisition process begins, checking the angle sensor correctness is es-sential as there will be no discrepancy between the real angle movement and the sensor's angle. The showed data by Rotary Encoder is compared to the goniometer to know how accurate the sensor is. Figure 3 illustrates how the validation of the elbow's angle using a goniometer is done.
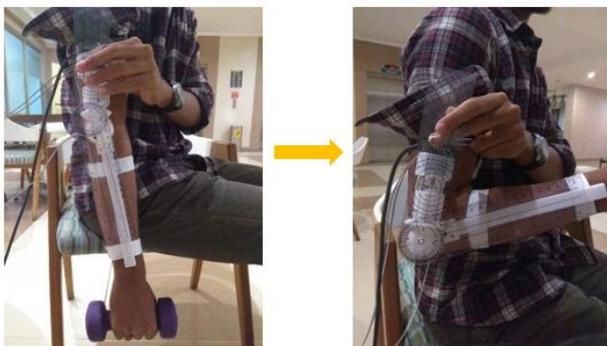

Figure 3 Validating elbow's angle using a goniometer

After that, the LabVIEW program, which comprises block diagrams and a user in-terface, is prepared to record both EMG signal and angle data. Both data are equipped with a timestamp and saved in comma-separated values (.csv) format. The subject will be asked to lift the 2 kg barbell vertically. Then, the subject is expected to do flexion and extension slowly and as smooth as possible for around 20 seconds. This research had set the LabVIEW to had a 10 kHz sampling rate, resulting in approximately 200,000 data for 1 data set. The reason for choosing 20 seconds for 1 data set is to avoid muscle fatigue due to lifting a heavyweight over and over. Meanwhile, a 10 kHz sampling rate is chosen for limiting the data loss of the EMG signal. Furthermore, more settings are applied to adapt the data acquisition device (NI MyDAQ) and the laptop; for instance, sample size is 500 and the buffer size 12,000. All these settings are expected to give detailed information of the EMG signal and the angle data, support the data acquisition easily, and minimalize the data loss.

2.1.2 Block Diagram of LabVIEW Program

In general, programming block diagrams in LabVIEW is the same as text-based programming, which consists of program initialization, looping program, and clear-ing/closing program. First of all, program initialization of gathering EMG signal data is set to have these functions: Task Channel DAQmx, Timing DAQmx, Buffersize DAQmx, and dan Start DAQmx. In Task Channel DAQmx, the constants are meant to regulate the data unit scale, the minimum and maximum input data voltage limits, the name of the EMG data variable, the type of terminal configuration, and control on the front panel to adjust the input channel. Furthermore, in the Timing DAQmx function, the constants set clock counting type and some controls on the front panel to adjust the sample size, sampling frequency, and data sampling type. The front panel to adjust the buffer size when retrieving data is controlled by Buffersize DAQmx function.

Moving on to the block diagrams of the angle data retrieval, the functions are Task Channel DAQmx dan Start DAQmx. Task Channel DAQmx defines the size of the initial measurement angle, the data unit's scale, and some controls on the front panel to adjust the input channel and pulse/rev. The last block diagram, Get Time in seconds, is used as a timer program. Subsequently, all block diagrams are connected to the looping program.

Block diagrams of the looping program consist of ReadAnalog DAQmx, ReadDigital DAQmx, timer program, data logging program, and two indicators in the form of charts. ReadAnalog DAQmx is used to read the EMG signal as an input and connected parallel with the Timing DAQmx function's sample size. The output of those function is linked with the EMG chart resulting in a user interface to see the EMG signal. Meanwhile, ReadDigital DAQmx is used to read the input from the angle data of the elbow and the output connects with the angle chart. The timer and the logging data are in the Boolean condition's logic to activate on the front panel. The last block diagram, called the closing program, is the unification of the Close DAQmx and Clear DAQmx function. The complete block diagram is presented in Figure 4.
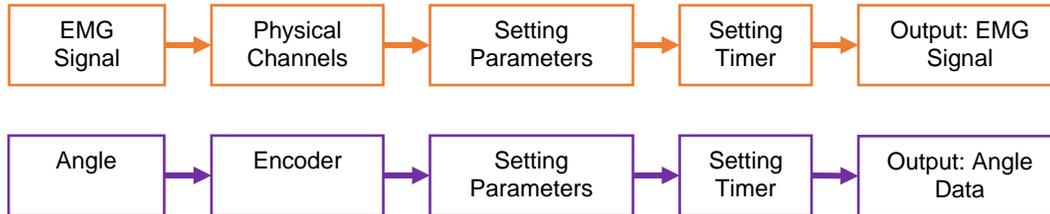

Figure 4 Block diagrams LabVIEW of EMG signal and angle data acquisition

2.1.3　Front Panel of LabVIEW Program

The LabVIEW program's front panel or user interface will be divided into groups matching the subfunction of controls or indicators. First, the front panel is arranged into an EMG signal acquisition subfunction, which consists of the setting parameterers, such as control input channel, sampling mode, sampling frequency, sampling size, and buffer size. Secondly, the angle data acquisition subfunction manages encoder configuration consisting of channel control and pulse magnitude/rev. Thirdly, the timer count down's subfunction includes timer input control and numeric indicators. The fourth subfunction, logging data, is to control file path data. The last Boolean subfunction regulates the activation of timer count down, data logging, and program termination.

2.2　EMG Signal and Angle Data Prerocessing

2.2.1　EMG Signal Prerocessing

Defining the offset point of EMG is the first thing to do as it will give clear comprehension of the initial limit of the signal. The offset is 1.55 V, as shown as the first initial value of the EMG. The offset of the EMG can be seen in Figure 5.
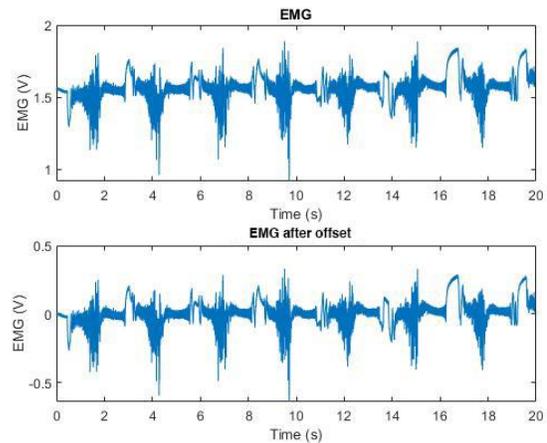

Figure 5 The changes of EMG signal because of the offset

Maeda [17], as demonstrated in Figure 6, stated that EMG signal lies on the fre-quency between 6 – 500 Hz with the highest amplitude in the range of 10 – 250 Hz. Thus, the filtering is conducted to get the EMG signal and eliminate the 20 Hz noise from the motion artifact electrode and/or 20 Hz noise from the cable [18].
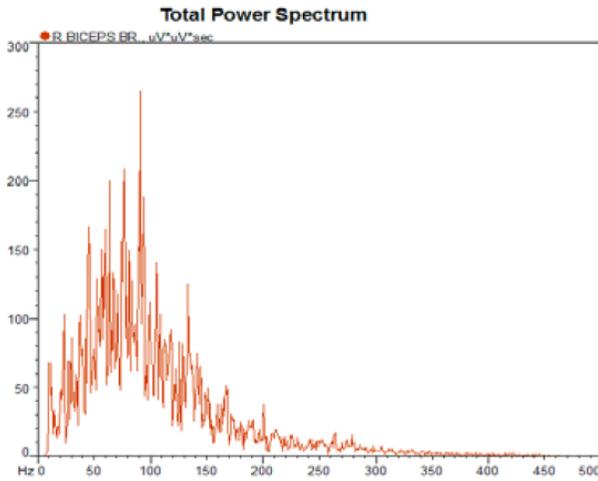
Figure 6 The most significant power spectrum of EMG lies on 10-250 Hz [17]

Figure 8 Before and after EMG's filtering with frequency domain

As a result, the second-order Butterworth type IIR Band Pass Filter is set to pass the frequency between 20 – 500 Hz. Next, a second-order Butterworth type IIR Band Stop Filter with a frequency between 49 and 51 Hz is applied to eradicate the noise from Power Line Interference (PLI). Figure 7 presents the changing of before and after the filter process.
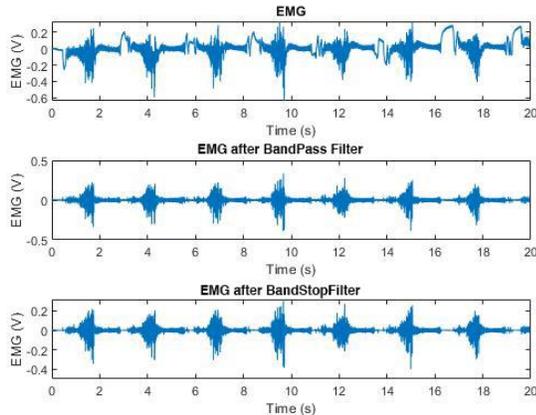

Figure 7 Before and after of EMG's filtering

After the filtering, EMG will be transformed from the time domain into the fre-quency domain using a Fast Fourier Transform (FFT) formula (2). This step will simplify our observation through the frequency filtering process, as well as Figure 8 shows.

$$F(\omega) = {}_{-\infty}\int^{\infty} f(x).e^{-i\omega x} \, dx \qquad (2)$$

Where,
ω = Frequency
X = Time

Afterwards, the next step of preprocessing EMG signal is rectifying the signal in order to get a positive value of the signal itself and doesn't contain a negative value or information of data. Ultimately, smoothing the EMG signal is the last step of all. Using moving average on formula (3) is the guidance of performing smoothing with 4,000 window size.

$$F(y_i)=1/(2N+1) \cdot \sum\nolimits_{k=1-N}^{k=i+N} y_k, \quad N < i < m-N \qquad (3)$$

Where,
y_i = Result of moving average
y_k = The value of the angle
N = Window size
m = The length of the data

2.2.2   Angle Data Preprocessing

The problem occurs when retrieving angle data because too many data have the same value on different timestamp. That is to say, drawing the graph from the data gathered will make a stair-like shape curve. This result forces the preprocessing step, which is smoothing, as mentioned in formula (3). The difference is, instead of using 4,000 window size, 1,000 window size is selected. The result can be observed in Figure 9.
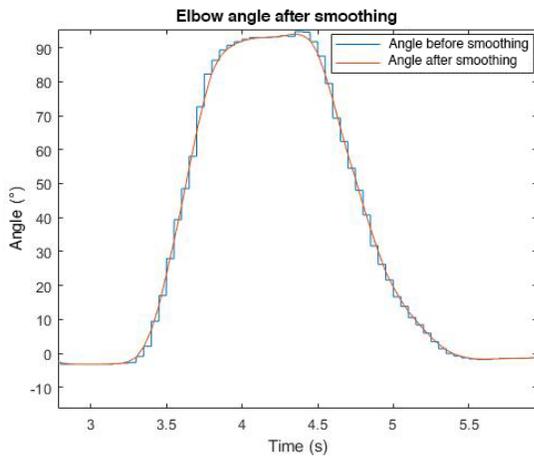
Figure 9 The result of smoothing angle data

2.3 Correlation and Modelling

Correlation is the measure of monotonic relation among two variables [19]. There are two types of monotonic relation for the details: (1) when one of the variables rises, the other variable value rises too, (2) when one the variable rises, the other variable value drops. The correlation value could also mean three states, which are positive, negative, and no correlation. That is to say, if the data do not correlate, the data will not be able to create the model, or the model will not represent between input and output. This study uses the formula (4) to determine the covariant EMG signal and angle data to get the value of the correlation coefficient.

$$\text{Cov}(X,Y) = \sum (x_i - x_{bar})(y_i - y_{bar}) / (n-1)$$
Where,
x = Value of the EMG
x_{bar} = Mean of the EMG
y = value of the angle
y_{bar} = Mean of the angle

$$\text{Corr}(X,Y) = (\text{Cov}(X,Y))/\sqrt{(\text{var}(X).\text{Var}(Y))}$$

or,

$$\text{Corr}(X,Y) = \sum (x_i - x_{bar})(y_i - y_{bar}) / \sqrt{(\sum (x_i - x_{bar})^2 . \sum (y_i - y_{bar})^2)} \quad (4)$$

After the correlation is set utilizing the previous formula, modelling the data is carried out. Curve fitting or non-linear regression method is selected. Rindengan and Mananohas [20] stated that if there are y data in many x data, the function $y = f(x)$ could be found that define the nearest relation between y and x. This approach is called curve fitting in the numerical method, as shown in formula (5).

$$y = a_0 + a_1 x + a_2 x^2 + .. + a_n x^n$$
$$na_0 + (\sum x_i)a_1 + (\sum x_i^2)a_2 = \sum y_i$$
$$(\sum x_i)a_0 + (\sum x_i^2)a_1 + (\sum x_i^3)a_2 = \sum x_i y_i$$
$$(\sum x_i^2)a_0 + (\sum x_i^3)a_1 + (\sum x_i^4)a_2 = \sum x_i^2 y_i$$

$$(\sum x_i^r)a_0 + (\sum x_i^{r+1})a_1 + (\sum x_i^{r+2})a_2 \ldots + (\sum x_i^{r+r})a_r = \sum x_i^r y_i \quad (5)$$

2.4 Monte Carlo Simulation and Estimation

Both EMG signal and angle data are compared and analyzed the correlation with their covariant and also stipulated which kind of type the correlation they have, whether positive, negative or no correlation. Subsequently, the modelling is created from the EMG signal and angle data for the Monte Carlo simulation's first step. Analyzing the model's error will be part of the collating PDF step to generate a random value used in the Monte Carlo simulation. Monte Carlo simulation is a computerized mathematical technique that allows the researcher to estimate, calculate risk in quantitative analysis, and decide. The Monte Carlo simulation analyzes risks by building models from the random value of the probability function. Then, calculating over and over depends on the number of uncertainties dan the range set. Monte Carlo simulation could use thousands of calculations before it ends. In the end, the range of the estimation is analyzed to define the actual result of the estimation. Figure 10 illustrates the Monte Carlo simulation's flowchart, and Table 1 shows the PDF, CDF, and interval error of the angle model.
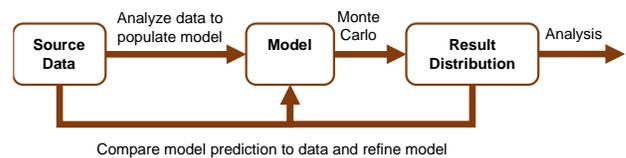

Figure 10 Monte Carlo simulation flowchart

Table 1 Illustration of PDF, CDF, and interval error of the angle model

No.	Error Angle model	Number of Data	PDF	CDF
1	0° - 5°	f1	f1/fX	f1/fX
2	6° - 10°	f2	f2/fX	(f1/fX)+(f2/fX)
3	11° - 15°	f3	f3/fX	(f1/fX)+(f2/fX)+
…	…	…	…	…
n	x-x(max)	Fx	fx/fX	1

Simulating angle with Monte Carlo needs some preparations. The first is the ini-tialization of the matrix, which its dimension consists of EMG signal for its row and the number of simulations for its column. Secondly, two looping programs are created, in which the first is to iterate row, and the other is to iterate the column. The first loop begins to calculate the angle's trend, deducting the second EMG signal data with the first EMG signal data. The trend will determine the direction of the angle that later will be utilized for angle estimation.

Meanwhile, the second loop will calculate the EMG signal's approximation as input using angle modelling. Afterwards, the Monte Carlo simulation

raises the random value representing the model's error and adds the value with the model's angle value. This second looping is conducted repeatedly, and this research repeats it 10,000 times.

According to Liu [22], in some cases, the Monte Carlo simulation would estimate reasonably if the repetition is in the range of 100,000 – 500,000 timer. However, a method to decide how many repetitions should be done is necessary, as shown in formula (6).

$$N = ((z.s)/\text{ø})^2 \tag{6}$$

where,

n = The number of Monte Carlo simulation
z = z-score value
s = Standard deviation
ø = Presision level

This study's confidence level is 95%; thus, the z-score will be 1.64, the standard de-viation will be 11.31, and the precision level will be 0.01. As a result, the number of repetitions for the Monte Carlo simulation will be roughly 3,500,000.

Unfortunately, because of the computation performance limitation and taking much time, based on Quinlan [23], the Monte Carlo simulation recommendation to analyze a model is 5,000 – 20,000 times. Hence, this study did the Monte Carlo simulation 10,000 times with resampling EMG signal and angle data 100 times to make the simulation process much more manageable. That is because the simulation is only repeated 10,000; the precision level decreases to 0.18.

2.5 The Analysis of The Result Data

Arranging data from angle estimation responding to EMG signal input is the analysis step of this research. The data from the previous testing will be plotted as an estimation response graph. The graph that has been produced will be analyzed based on the theory of estimation response. This analysis focuses on the characteristic of response estimation, especially on the angle estimation discrepancy with the real angle in each cycle.

3.0 RESULTS AND DISCUSSION

3.1 Retrieval Data Result

While collecting the data is under progress, the problems occur as the digital pin of DAQ is not fast enough to read and log the data in rapid frequency. The result of the angle data becomes not fulfilled as complete as the EMG signal. To address this problem, filling the blank angle data is performed with the previous data. Table 2 describes one of the retrieval data processes with the data file named day2_01042020_mark_3.

Table 2 EMG and elbow angles data acquisition results

No.	EMG (V)	Angle (°)	Real time (s)
1	1.556341	0.00	0.0001
2	1.555365	0.00	0.0002
3	1.555365	0.00	0.0003
4	1.55504	0.00	0.0004
5	1.55504	0.00	0.0005
.	.	.	.
.	.	.	.
.	.	.	.
199496	1.64379	36.74	19.9496
199497	1.64574	36.74	19.9497
199498	1.646066	36.74	19.9498
199499	1.652567	36.74	19.9499
199500	1.654518	36.74	19.95

3.2 Preprocessing Result

The first preprocessing data is the EMG signal. EMG signal is filtered by se-cond-order Butterworth type IIR Band Pass Filter with the range of frequency from 20 to 500 Hz. This range of frequency is applied because it is included in the range of EMG signal and automatically eradicate the noise of baseline wander and motion artefact. These noises are below 20 Hz. Having been filtered with a bandpass filter, the signal will be filtered again from 49 to 51 Hz by a second-order Butterworth type IIR Band Stop Filter to eliminate the PLI noise. Next, the EMG signal is rectified based on the offset. The offset itself is the EMG signal's modus, assumed as the 0 value of the EMG signal. The last step of EMG signal preprocessing is smoothing with moving average function. Figure 11 illustrates the changes in the EMG signal after the rectifying and smoothing process.
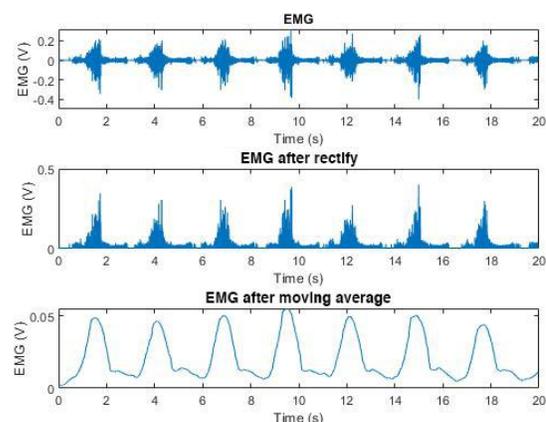

Figure 11 EMG signal condition when rectifying and smoothing is applied

The second step of preprocessing is the normalization of preprocessed EMG signal and angle data to shape the data distribution and the correlation between them graph-ically. Figure 12 shows the normalization result of both data.
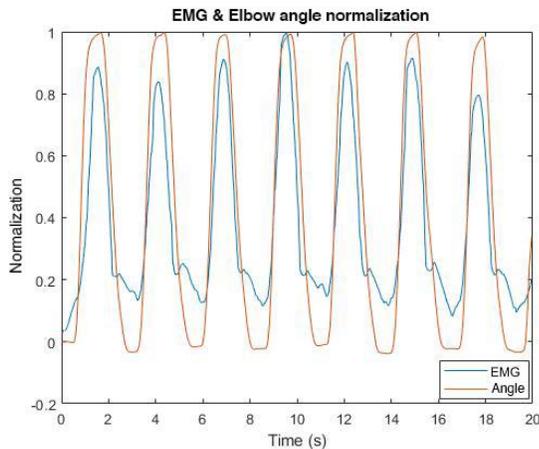

Figure 12 The normalization of EMG signal and angle data

3.3 Correlation and Modelling Result

Having been preprocessed, both data, EMG signal and angle data, will be modelled modestly. However, the correlation between both data will be calculated first.

The covariant value between EMG signal and angle data is 0.53. This value means that the EMG signal is positively correlated with the angle of the

elbow. Subsequently, the covariant value is scaled between -1 and +1, in which 0 means no correlation and the correlation is stronger nearing absolute 1 [19]. As a result, the correlation value is 0.95, which strongly correlates with EMG signal ad angle data. Table 3 shows 6 data set of its covariant and correlation coefficient.

Table 3 Covarian and Correlation Coefficient of 6 data set

No.	File data name	Covarian	Correlation coefficient
1	day2_01042020_mark_3	0.535039426	0.956477602
2	day2_01042020_mark_2	0.506191975	0.949994311
3	day2_01042020_mark_4	0.643063038	0.948693627
4	day2_01042020_mark_5	0.710900829	0.945847786
5	day2_01042020_mark_6	0.904871409	0.930878271
6	day1_31032020_mark_17	0.732912809	0.906409784

In the modelling stage, the curve fitting method is used in this research utilizing MATLAB 209a. The result of the modelling is f(x) = 43.38 - 1.56E+04x + 1.82E+06x^2 - 9.88E+07x^3 + 3.10E+09x^4 - 5.09E+10x^5 + 3.28E+11x^6, with RMSE is 8.02°. The model is based on one subject. In other words, this model will be adaptable to other subjects with other variables. Table 4 depicts three models with the least RMSE, while Figure 13 shows the comparison between the models and the measured angle.

Table 4 Models with the least RMSE result

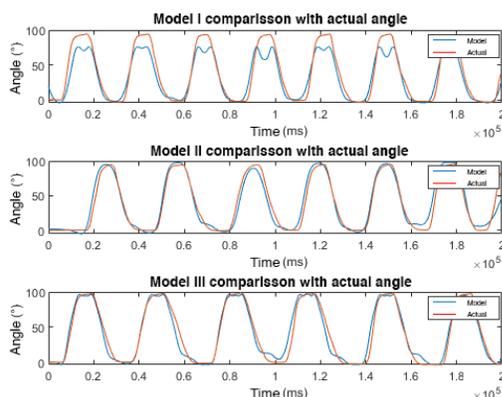| No.	File data name	Model	RMSE (°)
1	day2_01042020_mark_3	f(x) = 43.38 - 1.56E+04x + 1.82E+06x^2 - 9.88E+07x^3 + 3.10E+09x^4 - 5.09E+10x^5 + 3.28E+11x^6	8.026
2	day2_01042020_mark_2	f(x) = 17.79 - 7528.93x + 7.42E+05x^2 - 2.01E+07x^3 + 1.98E+08x^4 - 1.55E+07x^5 - 7.59E+09x^6	8.119
3	day2_01042020_mark_4	f(x) = 3.014e+11 *x^6 -6.1e+10*x^5 + 4.899e+09 *x^4 -1.983e+08*x^3 + 4.173e+06 *x^2 - 3.877e+04*x + 123.9	8.122

Figure 13 Comparison between models and measured angle

3.4 Monte Carlo Simulation

Monte Carlo simulation is a method to estimate a value or condition from its simulation, which in its usage depends on a random value. The result of Monte Carlo depends on the previously gathered data and arranged from the probability value; the higher the number of the simulation, the better the result of the estimation [21].

Bihani [21] contended that PDF is a realistic way to describe uncertainty from an analysis. The angle model's error PDF graph informs that the angle model's error closes to the normal distribution. All those descriptions can be seen in Table 5 and Figure 14.

Table 5 PDF and CDF from the error of angle model

| No.	Error angle model	Amount of data	PDF	CDF
1	-21° – (-18°)	2001	0.01003	0.01003
2	-18° – (-15°)	3900	0.01955	0.02958
3	-15° – (-12°)	5201	0.02607	0.05565
4	-12° – (-9°)	5799	0.02907	0.08472
5	-9° – (-6°)	4700	0.02356	0.10828
6	-6° – (-3°)	10599	0.05313	0.16141
7	-3° – (-0°)	35890	0.1799	0.34131
8	0° – 3°	25097	0.1258	0.46711
9	3° – 6°	15199	0.07619	0.5433
10	6° – 9°	15701	0.0787	0.622
11	9° – 12°	16600	0.08321	0.70521
12	12° – 15°	13500	0.06767	0.77288
13	15° – 18°	11199	0.05614	0.82902
14	18° – 21°	13201	0.06617	0.89519
15	21° – 24°	8600	0.04311	0.9383
16	24° – 27°	3399	0.01704	0.95534
17	27° – 30°	2300	0.01153	0.96687
18	30° – 33°	3601	0.01805	0.98492
19	33° – 36°	3002	0.01505	1
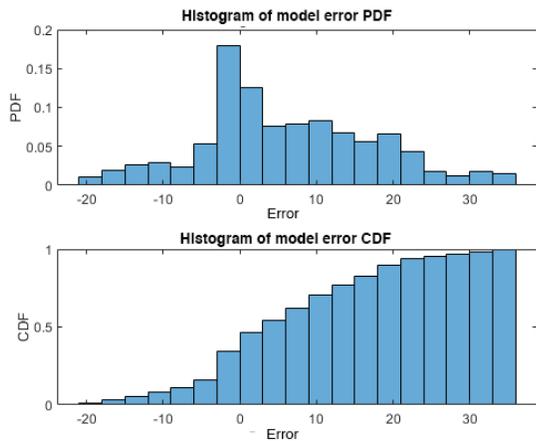
Figure 14 The histogram of PDF and CDF error model
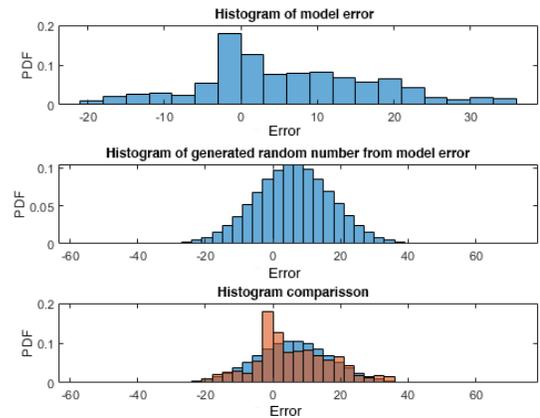

Figure 15 The bar chart comparison of PDF between error model and random value error model

Afterward, to generate the reasonable random value and to represent the error model, calculating the mean and the standard deviation is performed. The mean of the error model is 6.08, with a standard deviation of 11.31. Then the random value is generated as much as 10,000 values, and the assumption is that it is generally distributed with the mean and standard deviation as mentioned. This step produces a random value that resembles the error model. Thus, it could be presumed that the random generating value is valid for the Monte Carlo simulation. Figure 15 illustrates the comparison of PDF between the error model and the random value error model.
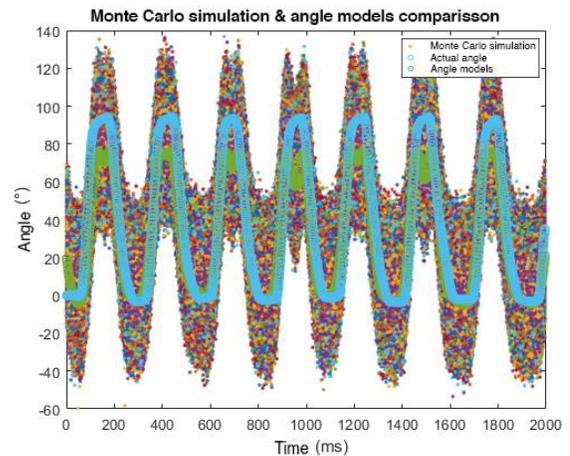

Figure 16 Monte Carlo simulation result

After the Monte Carlo simulation is performed, in Figure 16, some points show precisely the same as the measured angle. The comparison between the simulation and the angle model shows that the Monte Carlo simulation produces better angle approximation than the angle model.

3.5 Angle Estimation

This research also estimates the angle from the approximation that has been done in the Monte Carlo simulation. First, limiting and defining estimation range from the Monte Carlo simulation data is needed expecting the result of angle estimation to more accurate. Lee *et al.* [24] estimated Minimum Mortality Temperature (MMT) as a point and an interval using Monte Carlo simulation. The result showed an excellent estimation with 95% of accuracy when he defined the range. Lerche and Mudford [25] also suggested checking the previous data so that the accuracy will be higher and the data will be converged. The angle range limitation will be decided by the angle's trend (the difference between the recent model and the previous model), previous angle estimation, error estimation, and previously measured angle.

In the angle estimating stage, the range will be divided into four groups, which are angle's trend is positive and previous error estimation is positive; angle's trend is optimistic and previous error estimation is negative; angle's trend is negative and previous error estimation is positive, and angle's trend is negative and previous error estimation is negative. To estimate, the first thing to be seen is whether the angle's trend is positive or vice versa. The error estimation could then be classified into the category range with the difference between the recent and previous models.

After defining the category range, the Monte Carlo simulation value will be searched based on that range. The calculation of mean also will be done on the value of the Monte Carlo simulation, in which the result will represent the value of angle estimation. To estimate Value at Risk (VaR), Pradana *et al.* [26] used the mean of the Monte Carlo estimation.

The number of Monte Carlo estimation done also impose the result of the estimation and the number of blank estimation (cannot be calculated by the estimation). A specific range causes the estimation's blank value; there is no value from the Monte Carlo simulation. Table 6 depicts the relation between the number of Monte Carlo simulation and the blank value of the estimation, which is the higher the simulation, the lower the blank value.

Table 6 The comparison between the number of simulation and the blank value

No.	Amount of Monte Carlo simulation	Amount of the blank angle estimation value	RMSE of estimation angle (°)
1	10	1239	3.6225
2	100	635	2.0765
3	1000	329	1.8146
4	10000	151	1.7672

Simulation and estimation that have been done are performed toward the training data from the model itself. RMSE will test the performance of the estimation. The value of the RMSE could describe the accuracy of the estimation. Triwiyanto *et al.* [27] utilized Pearson Correlation, a coefficient, to measure the linear relationship's strength between predicted angle and measured angle. Thus, the three models will be tested, and all the error models have a correlation value of more than 0.80. Having been tested with 24 data set testing, the $f(x) = 17.79 - 7528.93x + 7.42E+05x^2 - 2.01E+07x^3 + 1.98E+08x^4 - 1.55E+07x^5 - 7.59E+09x^6$ model is the best model with the mean of RMSE is 8.96°, the mean of the lowest is 9.04E-05, the mean of the most significant error is 46.90°, and the mean of the correlation coefficient is 0.96. Figure 17 illustrates the comparison of angle estimation and simulation.
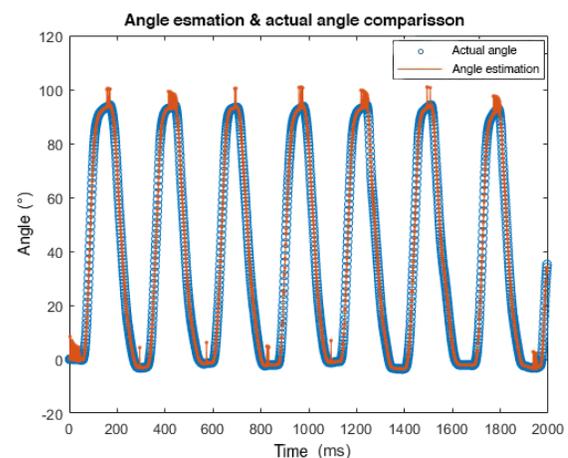

Figure 17 The comparison of angle estimation and simulation

Therefore, this study encapsulates that the Monte Carlo simulation could optimise a model and increase the angle estimation accuracy. Based on the 24 data set testing, model f(x) = 17.79 - 7528.93x + 7.42E+05x^2 - 2.01E+07x^3 + 1.98E+08x^4 - 1.55E+07x^5 - 7.59E+09x^6 with Monte Carlo estimation is the optimal model with 10,000 simulation. This is because the result of RMSE is 8.96°, and the correlation coefficient between the estimated angle and measured angle 0.96.

Hence, when the estimation is applied in the rehabilitation for atrophy post-stroke patient with the help of exoskeleton will perform a good result as the system could estimate the angle from a patient with minimal EMG signal and help the patient to move with the exoskeleton. Therefore, the clinical test should be conducted in long term rehabilitation therapy for post stroke patients by implementing the Monte Carlo method to measure and analyze the efficacy of the rehabilitation systems.

This study has limitations where it only has one subject because muscles have different individual characteristics, especially the biceps brachii [28]. Therefore, even though they perform the same motor task, each individual's movement patterns will be different and unique [29]. So this study chose to focus on the algorithm to get the suitable estimation model to predict the elbow joint angle from the biceps brachii.

The Furthermore, a comparison with the previous researches shown in Table 7.

Table 7 Comparison with Previous Researches

No	Author	Datasets	EMG Channel(s)	Features Extraction	Estimation	Result
1.	Zhou *et al.* 2018 [12]	30 EMG signals (6 subjects, 5 trials each)	2 channels	mean absolute value (MAV), zero crossings (ZC), slope sign changes (SSC), and waveform length (WL),	support vector machine (SVM) regression model	RMSE=19.07% and Correlation coefficients =0.793
2.	Pang *et al.* 2015 [13]	50 EMG signals (10 subjects, 5 trials each)	1 channel	a passive serial element (SE), an active contractile element (CE), and a passive element (PE)	Hill-Type-Based Muscular Model	Biggest RMSE = 19.35 +/- 3.15 correlation coefficient is above 0.97
3.	Mamikoglu *et al.* 2016 [14]	4 subjects	16 channels	Unknown	auto-regressive integrated moving average with exogenous input (ARIMAX)	Fitness value > 0.9
4.	Doheny *et al.* 2007 [11]	12 subjects	3 channels	Root mean square (RMS), EMG median frequency	maximum voluntary contraction (MVC)	joint angle did not have a significant effect on the force–EMG relationship of the biceps (F = 1.03, P = 0.421) No significant effect of joint angle on Fmed was observed in the brachioradialis (F = 1.916, P = 0.09)
5.	Proposed method	52 EMG signals (1 subject, 52 trials)	1 channel	Curve fitting (non-linear regression)	Monte Carlo	RMSE = 8.96° Correlation coefficient = 0.96

4.0 CONCLUSION

This study shows that Monte Carlo simulation could optimize the elbow angle estimation from 1 channel EMG signal. After all data acquisition and preprocessing steps for both EMG signal and angle data, the modelling is performed with curve fitting (non-linear regression). Form the data analysis; the Monte Carlo simulation shows good accuracy from 24 data set testing. With the 8.96° RMSE and the 0.96 correlation coefficient, the Monte Carlo simulation could be categorized as excellent estimators for the elbow angle.

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