# Assessment of Stroke Severity Level Using EMG, EEG and ECG for Virtual Rehabilitation

Lim Choon Chen, Sim Kok Swee and Tan Shing Chiang

*Abstract*—**Stroke is a popular disease that brings concern to medical experts around the world. Thus, assessment of the stroke severity level is essential to make sure that the physiotherapists can assign the patients to suitable rehabilitation training. In this paper, stroke severity level of the stroke patients can be determined by using the combination of electromyogram (EMG), electroencephalogram (EEG) and electrocardiogram (ECG) measurements. The EMG, EEG and ECG signals will go through signal process to eliminate the unnecessary features of the signal. The power spectrums and frequencies of each biosignal are computed. The calculated outcome will be inserted into a matrix equation to compute a stroke vector (s) for determining the severity level of the patient. The stroke vector will be used to assign the patient with the appropriate virtual rehabilitation training. Two virtual rehabilitation training, which are 'Pick & Place' and 'Stone Breaker', are included in a program for stroke rehabilitation. This virtual rehabilitation program is useful to assist in the restoration of upper limb motor and fingers motor of stroke patients. A total of 40 stroke patients had joined the research study. 30 of them were recruited to join the biosignals testing for the formation of stroke vector equation using machine learning. Another 10 patients were assigned for the result testing of the developed system. The result had shown that the designed framework could effectively assign the patients to suitable virtual rehabilitation training through the stroke vector calculation. Besides, the stroke assessment system had achieved a high accuracy of 96.67% in determining the stroke severity level of stroke patients. By using the computerized stroke assessment method, it enhances the accuracy in the assessment of stroke severity level.**

*Index Terms*—**EMG, EEG, ECG, Stroke Severity Level, Virtual Rehabilitation**

## I. Introduction

Stroke is a disease in which the brain tissues suffer from damage. It is induced by an abnormality in the blood supply to the brain. Besides, stroke is a significant global health problem that can contribute to major morbidity and mortality [1]. Worldwide, stroke is ranked as the second commonest cause of death and the third most common cause of disability-adjusted life-years (DALYs). According to the World Health Organization, each year nearly 15 million people suffer from stroke worldwide. In this population, 5 million people die, whereas another 5 million people are permanently disabled [2]. In Malaysia, stroke becomes the second largest cause of death [3].

Several symptoms will appear before the stroke happens. The common symptoms are the numbness of face, arm and leg [4]. A sudden numbness, weakness or paralysis in the face, arm or leg are the warning before a stroke happens. Usually, stroke affects only one side of the body. Besides, the patient might also have trouble in speaking or understanding what others are saying. Moreover, possessing headache and trouble in walking are also signs before stroke occurs [4].

Stroke brings numerous negative effects to the patients. Among these negative effects, finger motor impairment and upper limb dysfunction are the major problems encountered by stroke patients [5]. In this way, finger motor impairments are common symptom faced by the stroke patient due to deficit in motor execution and failure of executing higher-order processes such as motor learning and motor planning. On the other hand, upper limb impairment is the inability of arm muscles to raise the impaired upper limb. These give rise to some negative effects such as affecting the patients' mobility, limiting their daily life activities and their participation in society. The daily living activities can be simple activities such as reaching, swallowing, walking, gripping, and dressing [6]. These factors result in a lower quality of life.

Therefore, assessment of stroke severity level is essential to allow the patients to understand their stroke condition from time to time. Besides, the physiotherapists or the doctors can assign the patients to the suitable rehabilitation training based on the quantification of stroke impairment. The most frequent technique used in the medical field is the National Institutes of Health Stroke Scale (NIHSS) [7]. It is a common method employed to objectively quantify the stroke severity level. The NIHSS comprises 11 items. These 11 items examine the patient's brain and arm muscle. Since the brain and muscle inspection are the effective way to quantify the stroke severity level. Each of the items has a score that is ranged from 0 to 4 [8]. In this case, 0 signifies normal function in that specific ability, whereas a higher score of 4 is the indicative of some level of impairment. The score is then summed to obtain a

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total NIHSS score. The highest total NIHSS score of 42 indicates the worst stroke condition, whereas the lowest total score of 0 means normal condition with no stroke [8][9].

Nevertheless, there are some drawbacks of using the NIHSS technique. The NIHSS consists of items with poor redundancy and reliability [10]. It is an assessment system that uses manual score recording method. In this way, the accuracy of the manual score analyzing system is low. All the NIHSS scores are given manually by healthcare providers. Favoritism which is caused by the human being might happen [10]. Besides, the assessment level of each different doctor can also lead to the inaccuracy of the result. Thus, a computerized method is introduced to minimize human error in the NIHSS method. In this way, a system of assessment on the stroke severity level using the combination of electromyogram (EMG), electroencephalogram (EEG) and electrocardiogram (ECG) is developed to assess the stroke condition of the patient. It is a brand-new approach to analyze the stroke condition by using the computerized analysis method. It allows the physiotherapists to assign the patients to the suitable rehabilitation training.

Electromyography (EMG) is a diagnostic method that is employed for evaluating the health condition of muscles and the motor neurons that control them [11]. When the muscle is contracting or relaxing, the motor neurons will transmit electrical signals. An EMG will translate these signals into numbers or graphs. It can ease the doctors in constructing a diagnosis. Besides, an electroencephalogram (EEG) is utilized to detect electrical activity in the brain. Brain cells can communicate with each other through electrical impulses [12]. Thus, EEG is adapted to detect potential problems associated with this activity. In this case, an EEG tracks and records brain wave patterns. On the other hand, electrocardiogram (ECG) is used to measure the heart rate of the subject. An electrocardiogram (ECG) is a medical evaluation that is customarily used to measure the electrical activity of a patient's heart [13]. It offers useful information about the patient's heart rate and rhythm. As a consequence, the doctor is capable of knowing whether the patient's heart is regularly working or not.

Hence, the participants are exposed to the EMG, EEG and ECG sensor measurements before the virtual training session. The outcome of EMG, EEG and ECG signals will be combined into the matrix equation to compute for the stroke vector (s). Then, the stroke vector can be used for determining the stroke severity level of the patient to assign the patient to the suitable virtual rehabilitation training. The two virtual rehabilitation training are 'Pick & Place' and 'Stone Breaker', which are designed for rehabilitation of upper limb impairment. Virtual rehabilitation is adopted instead of physical rehabilitation since virtual rehabilitation can boost the recovery rate of the patient. This is due to the reason that the gamified version of rehabilitation games encourages the patient to rehabilitate more frequently inside the immersive and attractive gaming environment [14].

## II. METHODOLOGY

### A. Data Collection Procedure

The patient needs to insert his or her personal general information of name, age, gender and basic stroke information in the developed system as demonstrated in Fig. 1.

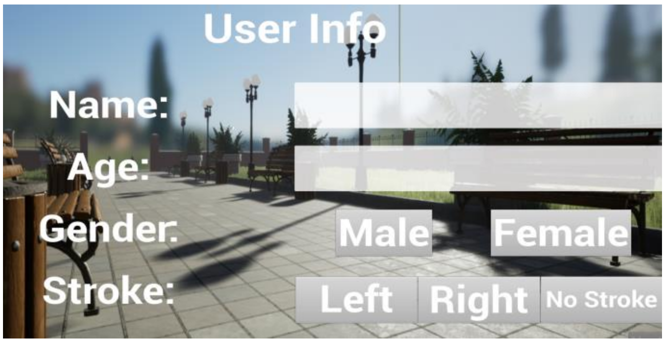



Fig. 1. User information record system

Then, the patient is exposed to the EMG, EEG and ECG measurements by using the specific sensors. For the EMG measurement, the sensor used is OYMotion analog EMG sensor. The first step involving in the placement of EMG sensor is thoroughly cleaning the intended area with soap to remove dirt and oil. Next, electrodes are snapped to the sensor's snap connectors. Then, the surface EMG sensor is attached at the bicep and arm (deltoid muscle area) of the impaired limb. Then the sensor is connected to the development board. In this case, the Arduino board is used to command the EMG sensor. It is also the link between the personal computer and the EMG sensor. When the setup is completed, the patient is asked to repeat raising and lowering down his impaired limb for 30 seconds [15]. This is done by taking the muscle electrical signal of the impaired arm. In this case, time measurement is limited 30 seconds since it is sufficient time to allow the patient carrying a few sets of raising and lowering the impaired limb [15]. Hence, a stable and average muscle signal can be obtained within this period. The stable muscle signal can be used for the analysis of muscle power. After that, the 'Processing' application is applied in order to write the output data to the spreadsheet for analyzing purpose.

In terms of EEG measurement, the stroke patient data is gathered by using the Emotiv Epoch (with 5 channels). The EEG sensor is attached to the scalp of the patient. Two sensors in the Emotiv Epoch are essential components. They are located in the sensor motor position at the brain and are in charge of movements. The sensor of T7 is used for the right-handed task whereas the sensor of T8 is employed for the left-handed tasks (note that if the task involves a right hand, the left part of the brain is responsible for the movement, and vice-versa). Fig. 2 shows these two channels.

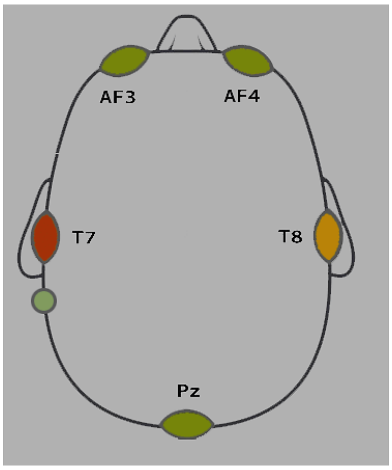


Fig. 2. The two channels signal of EEG

After the EEG headset is successfully set up, the patient is asked to raise his or her impaired arm up and down repeatedly for 30 seconds [15]. During this exercise, the EMG surface sensor is attached to the patient as well. EEG and EMG sensors are activated in parallel to record the brain signal and muscle signal. The EEG data is recorded into a spreadsheet.

During the ECG test, 3 electrodes with adhesive pads will be attached to the skin of arms, and legs. Right and left hand are respectively attached with one electrode while the left leg is attached with another electrode. In this case, the three electrodes can be differentiated by different color designs. The specific color of electrode only compatibles with specific organs of attachment. Wrong attachment of electrode triggers wrong ECG signal obtained. Fig. 3 displays the hardware setup for the ECG test.

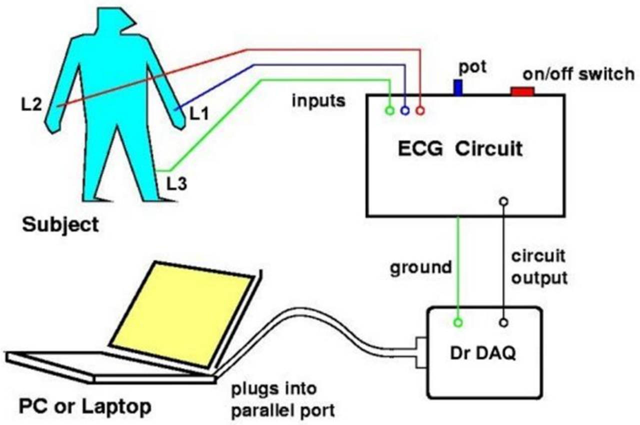


Fig. 3. ECG hardware setup

After that, the ECG sensor is attached to the patient for 2 minutes. This is done to take the resting heartbeat rate of the patient before the virtual reality training. Within 2 minutes, the patient does not need to do anything. This is due to the reason that the resting heartbeat rate is taken in order to determine the heart condition of the patient. In this case, 2 minutes is required because it is sufficient time for the heartbeat rate of the patient to reach a stable heartbeat state. A stable heartbeat signal is essential for data analysis. After 2 minutes, the signal is stored in the spreadsheet.

After that, EMG, EEG and ECG will be processed using some filtering methods such as high pass filtering, low pass filtering, bandpass filtering and Butterworth filtering. The biosignals of EMG, EEG and ECG need to undergo Fast Fourier Transform (FFT) to obtain the power spectrum and frequency of the signal. The power spectrum and frequency of each signal are then combined by a designed matrix equation to compute for the stroke vector (s) in tracking the stroke severity level of the stroke patient. The stroke vector will be utilized to determine that the patient is suitable for which type of VR rehabilitation training.

### *B. EMG Signal Processing*

For the data analyzing purpose, the raw EMG signal is needed to be filtered and modified. The raw signal is first shifted to the center of the axis. Then, full-wave rectification is applied to shift the bottom negative signal to the positive side to ease the analyzing process, as shown in Equation (1).

$$X = |EMG| \tag{1}$$

There is a way to capture the EMG envelope by computing the root mean square (RMS) value of the signal within a window which “slides across” the signal. The equation for calculating the sliding RMS is demonstrated in Equation (2).

$$X_{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}|X_n|^2}, \tag{2}$$

where $X_{RMS}$ refers to the sliding (RMS) value, $X_n$ refers to the value of X at position n and N represents the sample size. After that, the enveloped signal is then transformed by using Fast Fourier Transform function as illustrated in Equation (3).

$$X[k] = \sum_{n=0}^{N-1} x[n]e^{-2\pi jnk/N}, \tag{3}$$

where X[k] represents the complex number, x[n] is the value of X at position n and N refers to the sample size. After performing the FFT, there will be real and imaginary values. The real numbers represent the cosine correlation while the imaginary values represent the sine correlation. In order to calculate the power spectrum, we have to multiply the conjugate values of the signal as expressed in Equation (4).

$$P_x(f)^{EMG} = X(f)X^*(f) \tag{4}$$

In Equation (4), the X(f) represents the frequency domain of the signal x(t) while the X*(f) represents the complex conjugate part of X(f). After the FFT is carried out, the signal is then converted to the frequency form of the signal as displayed in Equation (5).

$$f^{EMG} = f_s \frac{(0:\frac{EMGfftlength}{2}-1)}{EMGfftlength}, \tag{5}$$

where the length of *EMGfftlength* is the data length of the EMG signal which is the number of columns is the Comma Separated Values (CSV) file and the $f_s$ sampling frequency which is 1000 Hz. The steps involving in the EMG signal analyzing in the correct sequence are shifting to center, full-wave rectification, computing RMS, applying FFT, obtaining power spectrum and frequency.

### C. EEG Signal Processing

The first signal processing step is DC offset removal. The EEG data acquired from the Emotiv Epoc is in floating-point format. They are obtained by using the unsigned 14 bits Analog to Digital Converter. Hence, there is a DC level in the signal. Since the data is in an unsigned form, the average DC level is considered as the zero level, the negative voltage will be sent as the positive values which are below the average level.

To remove the DC offset, the median of each row is obtained by using the MATLAB function median (matrix, dim). Then the raw EEG data is subtracted with the median that found in the entire data channels. Second, the slew rate is limited to 15 $\mu V$. This means the maximum changes of the consecutive data points are limited to be 15 $\mu V$. Besides, a 0.16 Hz first-order high-pass filter is used to remove the background signal and also removes any long-term drift. The equation of the high pass filter is described in the transfer function form as shown in Equation (6).

$$H(z)=\frac{\beta z-\beta}{z-\beta}, \tag{6}$$

where H(z) represents the transfer function of high pass filter and $\beta$ refers to the coefficient of the high pass filter. It is set to 0.992, in order to make the cutoff frequency to be 0.16 Hz. The filter equations in time function are presented in Equation (7) and Equation (8).

$$p(t)=\alpha x(t)+\beta p(t-1), \tag{7}$$
$$y(t)=x(t)-p(t), \tag{8}$$

where $\alpha$ and $\beta$ are the constant coefficients, $\alpha = 1-\beta$. $y(t)$ is the output, which is the filtered EEG data. $x$(t) is the raw EEG data.

An event-related potential (ERP) is the average of all trials collected for a single user. Different trials exhibit different potentials within the sensor, and by taking the average of all trials, the noise in the EEG signal can be suppressed. If we have N trials (k being the trial number and t being the time elapsed), then the event-related potential is computed as displayed in Equation (9).

$$x(t)=\frac{1}{N}\sum_{k=1}^{N}x(t,k) \tag{9}$$

A fast Fourier transform (FFT) is an algorithm that is used to compute the discrete Fourier transform (DFT) of a sequence [16]. Fourier analysis can convert a signal from its original domain (often time or space) to a representation in the frequency domain and vice versa. Before performing the FFT, the signal has to multiply with the window function to ensure no wrapping artifacts. The formulas of the window apply are expressed in Equation (10) and Equation (11).

$$w(n)=2\pi\frac{n-(\frac{N+1}{2})}{(N+1)} \tag{10}$$

$$Window=\frac{\sin w(n)^2}{w(n)} \tag{11}$$

After applying the window function with the EEG signal, the function expressed in Equation (12) is used to perform the FFT.

$$X\left[k\right]=\sum_{n=0}^{N-1}x_n e^{-i2\pi kn/N}, \tag{12}$$

where X[k] represents the complex number, x[n] is the value of X at position n and N refers to the sample size. Power frequency analysis is an EEG signal analysis method. Spectral parameters can be utilized for quantifying the pharmacological effects of anesthetics on the brain and the level of sedation. Since the EEG spectral analysis is significant, the performance of each frequency in the power spectrum regarding the detection of awareness is evaluated. Thus, the power of the frequency component is computed by using Equation (13). There will be real and imaginary values. The real numbers represent the cosine correlation while the imaginary values represent the sine correlation.

$$P_x(f)^{EEG}=X(f)X^*(f) \tag{13}$$

In Equation (13), the X(f) represents the frequency domain of the signal x(t) while the X*(f) represents the complex conjugate part of X(f). After the FFT is carried out, the respective one-sided frequency lay on the horizontal axis is calculated by using Equation (14).

$$f^{EEG}=f_s\frac{(0:\frac{EEGfftlength}{2}-1)}{EEGfftlength}, \tag{14}$$

where the length of *EEGfftlength* is the data length of the EEG signal which is the number of columns is the Comma Separated Values (CSV) file and the $f_s$ sampling frequency which is 1000 Hz. The steps involving in the EEG signal analyzing in a correct sequence are DC offset removal, high pass filter, computing ERP, applying window function, applying FFT, obtaining power frequency and obtaining frequency.

*D. ECG Signal Processing*

The RR interval of ECG signal is determined in order to calculate the heartbeat rate of the patient. It is the distance between two consecutive peak ECG signals. It plays a vital role in finding abnormalities of a signal. Heart rate can be measured by using the formula presented in Equation (15).

$$\text{Heart Rate (bpm)} = \frac{60}{\text{R-R Interval (seconds)}} \tag{15}$$

The average heartbeat rate for a healthy person is 72 beats per minute (bpm). Nevertheless, there will also be a possibility for the abnormal heart rate, including bradycardia and tachycardia. Bradycardia implies a resting heart rate of below 60 bpm, whereas tachycardia means a heart rate of above 100 bpm. Bradycardia and tachycardia are classified as heartbeat abnormality.

Heartbeat segmentation aims to identify the individual beats of an ECG signal. It is applied in the spatial features feature extraction method. The minimum and maximum heart rates of a normal person's ECG ranges between 60 and 100 beats per minute (bpm). At such ranges, a moving interval can be used to detect the R peak. The left border of the moving interval is the sum of the signal length in one period of an ECG signal with the maximum bpm and the location of the previous R peak. The right border is sum of the signal length in one period of an ECG signal with the minimum bpm and the location of the previous R peak:

$$LB_n = i_{n-1} + \frac{60}{BPM_{\max}} f_s, \tag{16}$$

$$RB_n = i_{n-1} + \frac{60}{BPM_{\min}} f_s, \tag{17}$$

where $LB_n$ is the left border of the moving interval for the $n^{th}$ ECG beat, $RB_n$ is right border of the moving interval for the $n^{th}$ ECG beat, $f_s$ is the sampling frequency and $i_{n-1}$ is the location of the previous R peak. The R peak is then the location of the maxima in that moving interval.

Heart rate normalization is performed whereby heart rates are to be normalized to 80 bpm. This preprocessing is required by the linear correlation method. The ECG signal is first run through the heartbeat segmentation algorithm to obtain the individual heartbeats. Discrete Fourier transform is then applied to the ECG beats as shown in Equation (18).

$$H(k) = \sum_{n=0}^{N-1} h(n) \exp\left(\frac{-j2\pi kn}{N}\right), \tag{18}$$

where $k$ is the frequency index corresponding to the digital frequency defined as $(kf_s)/N$ for $0 \le k \le N-1$. The ratio of signal length, α, is then obtained by using Equation (19).

$$\alpha = \frac{N_n}{N}, \tag{19}$$

where $N$ is the signal length in a period and $N_n$ is the signal length for a normalized ECG signal. For $\alpha > 1$, the heart rate of the input ECG is higher than 80 bpm, whereas $\alpha < 1$ means that the heart rate is lower than 80 bpm. A new scale of the sampling period, T, is then obtained:

$$T = \frac{T_s}{\alpha}, \tag{20}$$

where $T_s=(f_s)^{-1}$. The Fourier components are then reconstructed to obtain the normalized ECG signal using $T$:

$$h_n(n) = \sum_{k=0}^{K} |H(k)| \cos(2\pi k \frac{f_s}{N} nT_n + \angle H(K)), \tag{21}$$

For $0 \le n \le N_{n-1}$, where $K$ is the frequency index that corresponds to the highest digital frequency in the ECG frequency spectrum.

The use of linear predictive coding (LPC) in the feature extraction of ECG signals is based on the similarity of the quasi-periodic property of ECG to a phonetic segment of a speech. LPC is a technique of time series analysis that is used to predict future values of a signal as a linear function of previous samples. Equation (22) is used to calculate the expected value.

$$x[n] = -\sum_{i=1}^{p} a_i x[n-1], \tag{22}$$

where $x[n-1]$ are the previous values, $a_i$ are the LPC coefficients and $p$ is the order of the LPC. The difference between the predicted values and the actual values (the error of the estimate) is calculated using Equation (23).

$$e[n] = x[n] - x[n], \tag{23}$$

where $x[n]$ are the actual values. The Levinson-Durbin recursion is used to minimize the error and obtain the final LPC coefficients. A Fourier transform is then applied to the coefficients by using Equation (24).

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi k \frac{n}{N}}, \tag{24}$$

where X[k] represents the complex number, x[n] is the value of X at position n and N refers to the sample size. After performing the FFT, there will be a real and imaginary values. The real numbers represent the cosine correlation while the imaginary values represent the sine correlation. In order to calculate the power spectrum, we have to multiply the conjugate values of the signal as shown in Equation (25).

$$P_x(f)^{ECG} = X(f) X^*(f) \tag{25}$$

In Equation (25), the X(f) represents the frequency domain of the signal x(t) while the X*(f) represents the complex conjugate part of X(f). After the FFT is carried out, the signal is then converted to the frequency form of the signal as expressed in Equation (26).

$$f^{ECG} = f_s \frac{(0:\frac{ECGfftlength}{2}-1)}{ECGfftlength}, \tag{26}$$

where the length of *ECGfftlength* is the data length of the ECG signal which is the number of columns in the CSV file and the $f_s$ sampling frequency which is 1000 Hz. The steps involving in the ECG signal analyzing in a correct sequence are heartbeat rate calculation, heartbeat segmentation, heart rate normalization, applying LPC, applying FFT, obtaining power spectrum and obtaining frequency. The signal processing steps of all biosignals are summarized in Fig. 4.

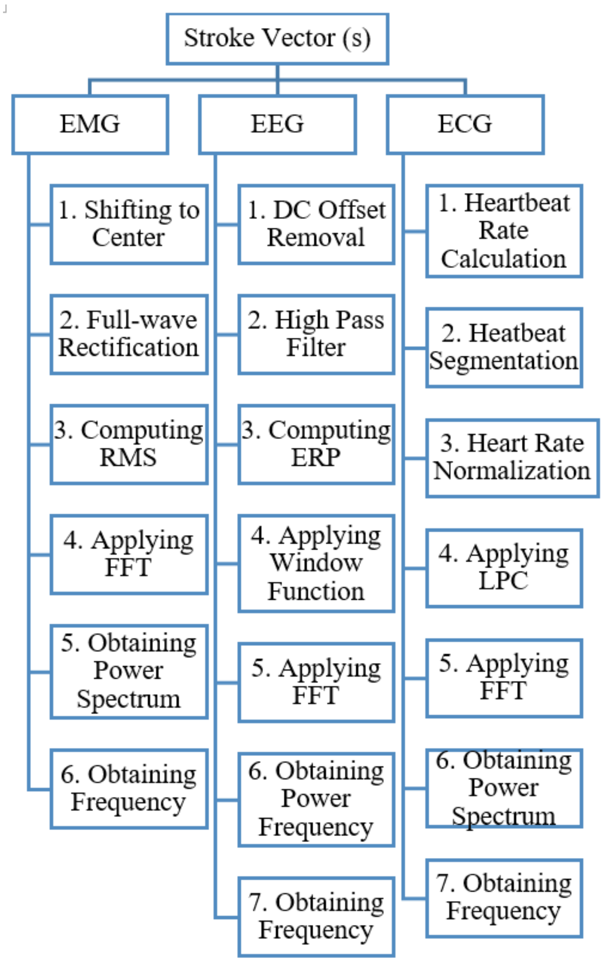



Fig. 4. Summary of signal processing steps for EMG, EEG and ECG

### *E. Stroke Vector Calculation (Combination of EEG, EMG and ECG)*

The biosignals of EMG, EEG and ECG undergo fast fourier transform (FFT). The common outputs of the biosignals are power spectrum and frequency. The power spectrum and frequency of each signal are then combined by a designed matrix equation to compute for the stroke vector (s) in tracking the stroke severity level of the stroke patient. The stroke vector will be utilized to determine that the patient is suitable for which type of VR rehabilitation training. First, matrix Equation (27) is applied in order to link three biosignals together.

$$y = ax \tag{27}$$

In this case, matrix vector $a$ is in a 2 x 3 order, matrix vector x is in a 3 x 2 order while $y$ is the desired output which is used to compute for the stroke vector (s). Matrix vector $a$ consists of the real part of the product of Fast Fourier Transform and the sampling frequency of each signal. Real values of FFT product occupy the first row whereas the sampling frequencies occupy the second row of the matrix vector $a$. Matrix vector $x$ consists of the imaginary part of the product of Fast Fourier Transform and the FFT length of each signal. Imaginary values of FFT product occupy the first column whereas the FFT lengths occupy the second column of the matrix vector $x$. Multiplication of the vector results in the output value $y$ with a 2x2 matrix. The multiplication of the matrix is shown in Equation (28).

$$\text{Let } b = \frac{(0:\frac{\text{length of } fft}{2}-1)}{\text{length of } fft}$$

$$y = \begin{bmatrix} X(f)^{EMG} & X(f)^{EEG} & X(f)^{ECG} \\ f_s^{EMG} & f_s^{EEG} & f_s^{ECG} \end{bmatrix} \begin{bmatrix} X^*(f)^{EMG} & b^{EMG} \\ X^*(f)^{EEG} & b^{EEG} \\ X^*(f)^{ECG} & b^{ECG} \end{bmatrix} \tag{28}$$

where $y$ is the output matrix, $X(f)$ is the real frequency domain values, $f_s$ is the sampling frequency, $X^*(f)$ represents complex conjugate part and $b$ represents the length of FFT of each signal. The result of the multiplication is presented in Equation (29).

$$y = \begin{bmatrix} u & v \\ w & x \end{bmatrix}, \tag{29}$$

where,

$$u = P_x(f)^{EMG} + P_x(f)^{EEG} + P_x(f)^{ECG}$$
$$v = [(b)X(f)]^{EMG} + [(b)X(f)]^{EEG} + [(b)X(f)]^{ECG}$$
$$w = [f_s X^*(f)]^{EMG} + [f_s X^*(f)]^{EEG} + [f_s X^*(f)]^{ECG}$$
$$x = f^{EMG} + f^{EEF} + f^{ECG}$$

where $P_x(f)$ is the power spectrum or the power frequency and $f$ refers to the frequency of each signal. This is due to the reason that the product of the real frequency part and complex conjugate part is the power spectrum. Besides, the product of sampling frequency and length of FFT gives rise to frequency unit. However, $v$ and $w$ do not provide any meaningful result which can contribute to the final stroke vector calculation. Thus, the value of diagonal of the matrix $v$ and $w$ are set to 0 to eliminate the unnecessary components of the matrix. The removal of diagonal of the matrix is shown in Equation (30).

$$y=\begin{bmatrix} P_x(f)^{EMG}+P_x(f)^{EEG}+P_x(f)^{ECG} & 0 \\ 0 & f^{EMG}+f^{EEG}+f^{ECG} \end{bmatrix} \quad (30)$$

The rest part of the matrix is an essential part of the step of computing for the stroke vector. Thus, the diagonal of matrix that consists of value of '0' should be eliminated since they do not bring any meaning. Thus, the step of removing the zero changes the 2x2 matrix into a single 2x1 matrix for the ease of analysis. Therefore, the output y has to multiply to the matrix with value of $\begin{bmatrix}1\\1\end{bmatrix}$ to transform into a 2x1 matrix. The result of the transformation is expressed in Equation (31).

$$y=\begin{bmatrix} P_x(f)^{EMG}+P_x(f)^{EEG}+P_x(f)^{ECG} & 0 \\ 0 & f^{EMG}+f^{EEG}+f^{ECG} \end{bmatrix}\begin{bmatrix}1\\1\end{bmatrix}$$

$$y=\begin{bmatrix} P_x(f)^{EMG}+P_x(f)^{EEG}+P_x(f)^{ECG} \\ f^{EMG}+f^{EEG}+f^{ECG} \end{bmatrix} \quad (31)$$

The y output component is a 2x1 matrix which comprises two summation equations. Thus, *y* matrix is broken down into two components of $y_1$ and $y_2$ as shown in Equation (32) and Equation (33).

$$y_1 = P_x(f)^{EMG}+P_x(f)^{EEG}+P_x(f)^{ECG}, \quad (32)$$

$$y_2 = f^{EMG}+f^{EEG}+f^{ECG}, \quad (33)$$

where $y_1$ refers to the total power spectrum of EMG, EEG and ECG while $y_2$ represents the total frequency of EMG, EEG and ECG.

Next, stroke vector (s) is used to evaluate the stroke condition of the patient from the result of $y_1$ and $y_2$ above. Thus, machine learning methodology is applied to learn from the available sample data set and derive a new equation to relate $y_1$ and $y_2$ in computing of stroke vector. In this case, machine learning builds heavily on statistics. Thus, in order to train the machine to learn, a statistically significant random sample is inserted as training data. If the training set is too small, it will lead to an inaccurate conclusion. Hence, 30 patients were recruited to join a test on EEG, EMG and ECG. The patients were randomized stroke patients, which meant some of them were severely stroke patients (n=10), some of them were moderate stroke patients (n=8) whereas some of them were having only light stroke (n=12). The massive data set was important to enhance the accuracy of the result. They were exposed to biosignals testing, upper limb power testing and Mini-Mental State Examination (MMSE) testing before conducting two virtual rehabilitation games. All the results and their capability of performing the rehabilitation games were recorded. The correspondence output value of $y_1$ and $y_2$ were calculated and imported into the MATLAB as an input for the machine to learn. The desired outcome of equation prediction was initialized with the stroke vector (s). In order to make a comparison between the predicting equation with the actual patients' stroke condition, the actual stroke conditions (including limb power, MMSE score, heart rate and capability of playing the games) of every patient were also inserted into MATLAB to set as a guideline for the machine learning to train. The machine learning would increase the accuracy for every time training until the difference error reduced to only 0.01. The result of machine learning training is shown in Equation (34).

$$s=\frac{6\sqrt{y_1 y_2}}{y_1+y_2} \quad (34)$$

Table I: The stroke patients' condition according to the computed (s) value.

| Stroke Vector (s) | Stroke Condition |
|---|---|
| S > 1 | - EMG: Excellent (upper limb power [a] ≥ 3)<br>- EEG: Excellent (MMSE [b] ≥ 24)<br>- ECG: Excellent (60 ≤ bpm [c] ≤ 100)<br><br>Rehabilitation training:<br>- 'Pick & Place' (all levels)<br>- 'Stone Breaker' (all levels) |
| S = 1 | - EMG: Moderate (upper limb power = 2)<br>- EEG: Moderate (18 ≤ MMSE ≤ 23)<br>- ECG: Moderate (50 ≤ bpm ≤ 59 & 101 ≤ bpm ≤110)<br><br>Rehabilitation training:<br>- 'Pick & Place' (Level 1)<br>- 'Stone Breaker' (Level 1) |
| S < 1 | - EMG: Poor (upper limb power < 2)<br>- EEG: Poor (MMSE < 18)<br>- ECG: Poor (bpm < 50 & bpm > 110)<br><br>Rehabilitation training:<br>- 'Pick & Place' (no)<br>- 'Stone Breaker' (no) |

Note: [a] Power of upper limb (measured by doctor); range: 0-5; high: better. [b] MMSE = Mini-Mental State Examination; range: 0–30; high: better. [c] bpm = beats per minutes; 60 bpm – 100 bpm: normal; 50 bpm – 60 bpm & 100 bpm – 110 bpm: moderate; <50 bpm: bradycardia (poor): >110 bpm: tachycardia (poor).

Table I shows the stroke patients' condition according to the computed (s) value. All the stroke conditions resulted from the stroke vector calculation are defined based on the initial condition of the 30 patients.

The stroke vector is calculated so that the patient can be assigned to the suitable rehabilitation training to ensure their safety in the rehabilitation training. If the computed (s) value is larger than 1, it implies the impaired upper limb can move. This is due to the reason of the power of the upper limb is at least 3. Besides, the patient has a healthy mind with the Mini-Mental State Examination (MMSE) score of at least 24. Moreover, the patient's heart is in excellent condition with the normal heartbeat rate within a range of 60 bpm to 100 bpm [17]. Other than that, the patient suffers from first time ischemic or hemorrhagic cerebrovascular accident. Thus, the patient (with s > 1) is allowed for the 'Pick & Place' training (all levels) and 'Stone Breaker' training (all levels).

If the computed (s) value is equal to 1, it means that the power of the upper limb is equal to 2. Thus, the impaired arm can slightly raise. Besides, the patient has a moderate level of mind with Mini-Mental State Examination (MMSE) score of more than or equal to 18 and less than or equal to 23. Moreover, the patient's heart is slightly weak (with the heartbeat rate within 50 bpm to 59 bpm and 101 bpm to 110 bpm) [17]. Therefore, the patient (with s = 1) is allowed for part of the virtual rehabilitation training. In this way, the patient is only permitted to play 'Pick & Place' (Level 1) and 'Stone Breaker' (Level 1). This is because Level 2 of 'pick & Place' consists more blocks to be picked up and Level 2 of 'Stone Breaker' consists more stones to be broken. Thus, Level 2 of both games are intense exercises that require more muscle force. In this way, poor muscle signal that is measured by EMG signifies that the patient's muscle is weak, so he is not able to raise his upper limb for a long time. Besides, poor heartbeat does not support for the intense exercise.

If the computed (s) value is smaller than 1, it identifies the power of upper limb less than 2. Thus, the impaired upper limb cannot move or the impaired arm cannot raise. Besides, the patient has the worst Mini-Mental State Examination (MMSE) score of less than 18. Apart from that, the heart is feeble (with a heartbeat rate of lower than 50 bpm and higher than 110 bpm) [17]. Therefore, patient (with s < 1) is not allowed for all the virtual rehabilitation training. This is because that poor muscle cannot move at all. The poor heartbeat rate of the patient is not suitable for intense exercise. Poor brain signal results in the problem in understanding the whole gameplay method.

### F. Virtual Rehabilitation Training

Virtual rehabilitation training is chosen as a method of rehabilitation since it is able to enhance the recovery rate of the stroke patient. Besides, the gamified version of virtual rehabilitation provides the patients with an immersive and attractive environment. Hence, the patients tend to carry out the rehabilitation training more frequently.

'Pick & Place' is a virtual rehabilitation training that is designed to rehabilitate the impaired fingers motor. It targets to enhance the gripping strength of the patient. It requires the patient to pick up the virtual block and stack it according to the sequence of largest at the bottom to smallest at the top. Leap Motion sensor is used to detect the fingers of the patient. Unity software is chosen as a platform to run the program. There are 3 levels with Level 1 consists of 2 blocks, Level 2 comprises 3 blocks and Level 3 contains 4 blocks. Fig. 5 illustrates the demonstration of 'Pick & Place'.

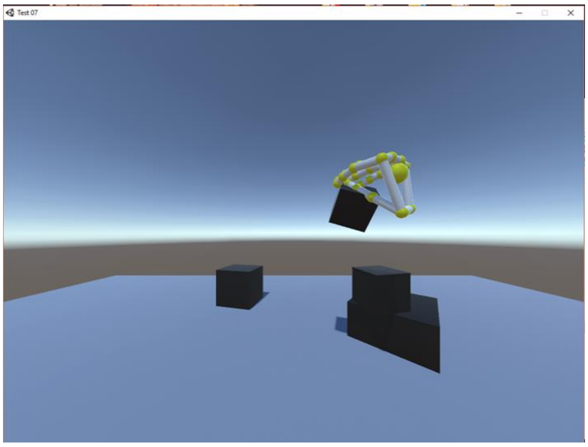


Fig. 5. Demonstration of 'Pick & Place' Level 3

'Stone Breaker' is another rehabilitation training that provides the function in rehabilitating the impaired upper limb of the patient. It is designed to increase the range of motion of arm. This application requires the patient to move their impaired upper limb to control the virtual paddle inside the screen. The paddle is moved to catch the moving ball and reflect it to the opposite side to break down the stones. Successful breaking of the stones will proceed the player to the next higher level. The game will be halted when all the lives are used up. However, the additional lives can be obtained by breaking the green stone. Besides, the breaking of blue stone contributes 1 point whereas the breaking of red stone gives 2 points. There are three levels of difficulty with each level contains different numbers of stones. Microsoft Kinect sensor is opted to sense the movement of the upper limb. Besides, Microsoft Visual Studio is a platform for the running of 'Stone Breaker' application. Fig. 6 depicts three different levels of 'Pick & Place'.

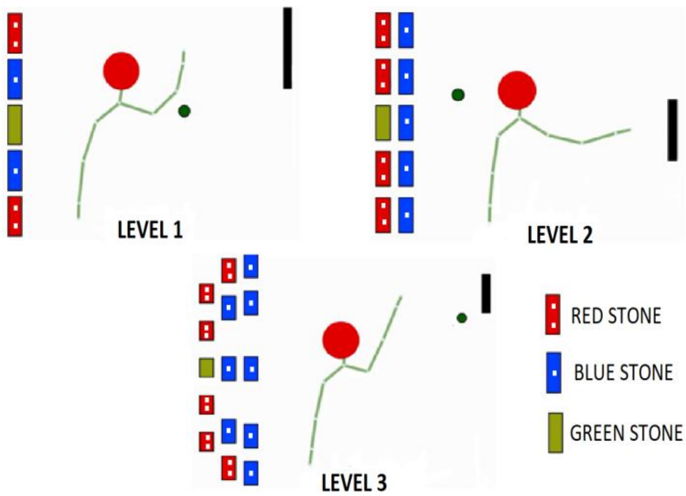



Fig. 6. Three different levels for 'Stone Breaker'

## III. RESULTS

There were a total of 40 patients recruited to join the experimental study. Out of the 40 patients, 30 of them were invited to join the biosignals testing for the formation of the stroke vector equation as mentioned earlier. Another 10 patients were assigned for the result testing of the developed system. There were average number of males (n=5) and females (n = 5) with an average age of 45.3 years old. Besides, 5 of them were left-sided stroke whereas another 5 were right-sided stroke. The patients were explored to biosignals measurement to determine the stroke vector value. Next, the patients were invited to play virtual games. Lastly, they were explored to upper limb power test, MMSE test and heartbeat test in order to evaluate the accuracy of the system. Biosignals of Patient C were opted as the sample in signal processing steps since his biosignals data exhibited the most stable signal.

### *A. EMG Signal Processing*

The EMG sensor was attached to the bicep and arm for 30 seconds. For every lifting of the limb, there was a visible fluctuating electrical signal that was produced by the muscle. The raw data of 10 patients were inserted to the MATLAB for data analysis purpose. Fig. 7 demonstrated the example of a fully-rectified EMG raw signal.

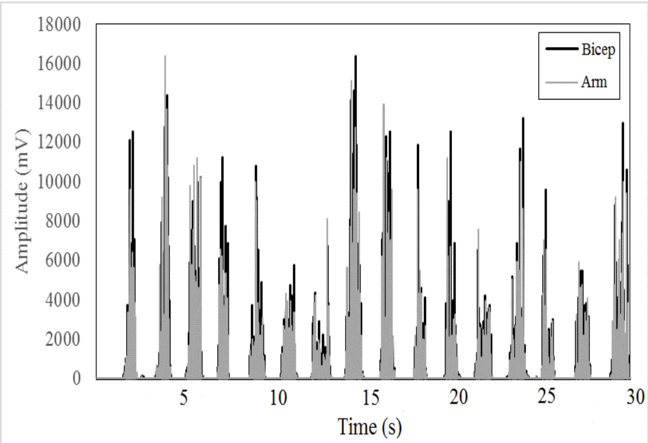



Fig. 7. Fully-rectified EMG signal of Patient C

Fig. 7 demonstrated the EMG signal of Patient C. Apparently, Patient C raised his arm for 16 times within 30 seconds. The signal was then undergone through a smoothing technique of application of sliding RMS. It would filter out extreme values such as huge noise interference. Fig. 8 depicted the graph of the EMG sign after applying the sliding RMS for Patient C.

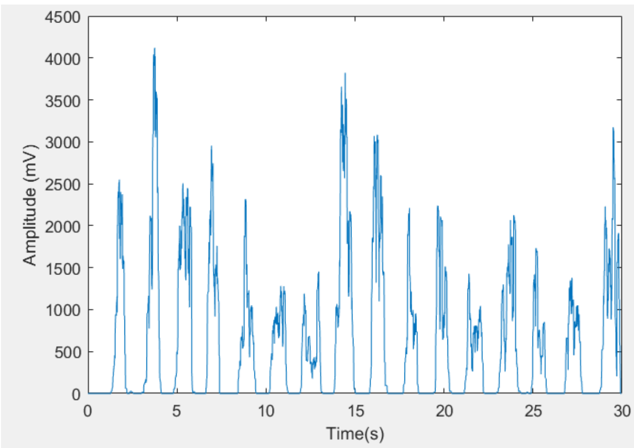



Fig. 8. EMG after applying sliding RMS filter of Patient C

Fast Fourier Transform (FFT) was then applied to the resulting data after the filtration. The graphical result of FFT for EMG signal was presented in Fig. 9. The power spectrum of the signal and the frequencies were computed based on the Equation (4) and Equation (5) in Section II Part B.

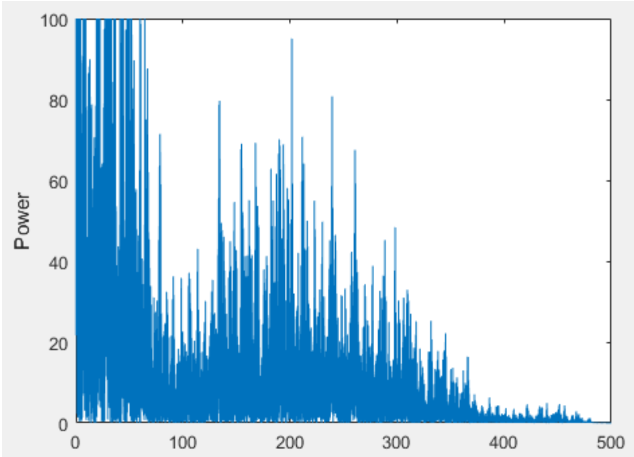



Fig. 9. EMG after applying FFT of Patient C

### *B. EEG Signal Processing*

Within 30 seconds, the patients were instructed to lift their limb. The raw data were then analyzed in MATLAB. Some signal processing steps of DC offset removal, high pass filtering and computing ERP were applied to the raw EEG data. The resulting EEG signal (after applying 3 signal processing steps) of Patient C was described in Fig. 10.

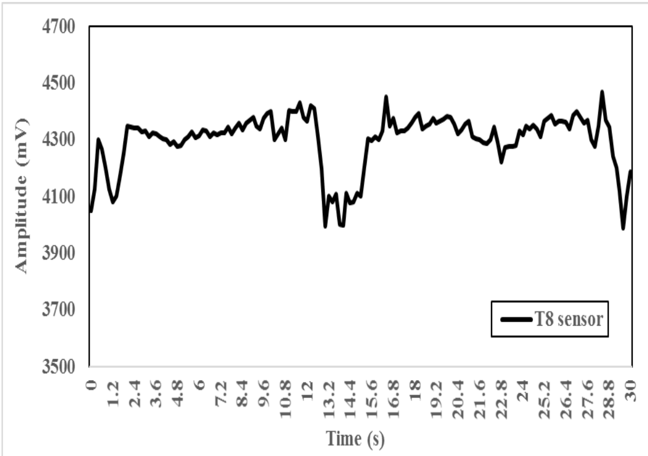



Fig. 10. EEG signal after 3 processing steps (Patient C)

There were five different channel signals measured by the EEG sensor. However, only T7 and T8 signals were considered as important brain signals for the calculation of stroke vector. Since Patient C was a left-sided stroke patient, therefore the signal indicator of T8 sensor was very obvious. There was no line for T7 sensor for the reason that the right brain of Patient C was not activating. Thus the T7 sensor gave an extremely low value which could be neglected in the graph.

Then, the Fast Fourier Transform (FFT) was applied to the resulting data. The graphical result of FFT for EEG signal was shown in Fig. 11. The power spectrum of the signal and the frequencies were calculated according to the Equation (13) and Equation (14).

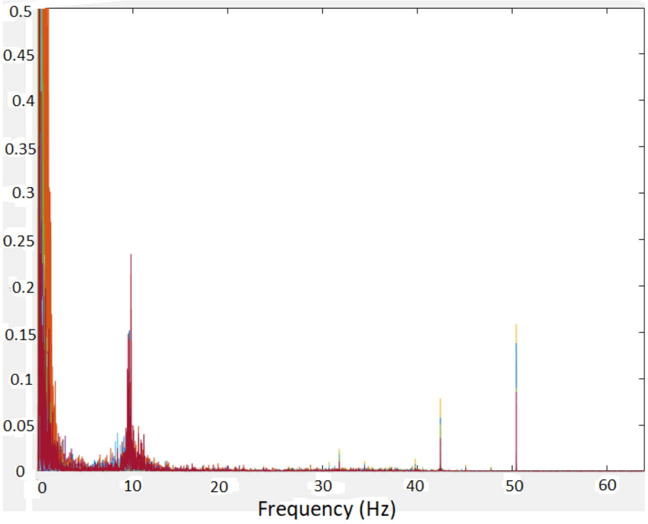



Fig. 11. EEG after applying FFT of Patient C

*C. ECG Signal Processing*

The patients were exposed to ECG measurement in the resting condition. The raw data were then inserted into the MATLAB for data analysis purpose. The ECG raw signal of Patient C was plotted in Fig. 12.

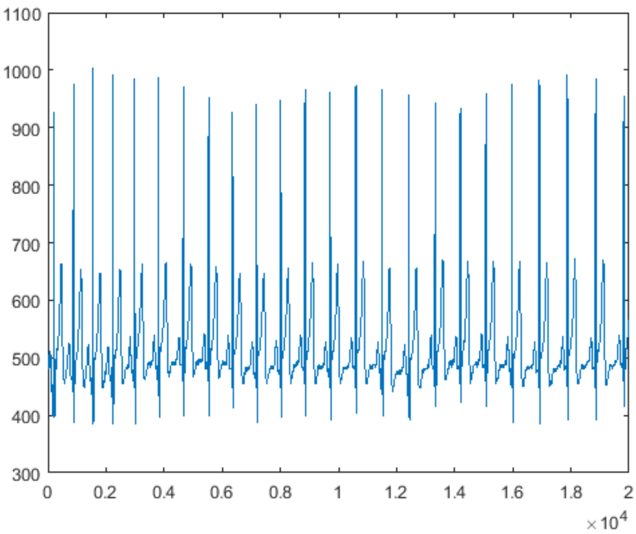


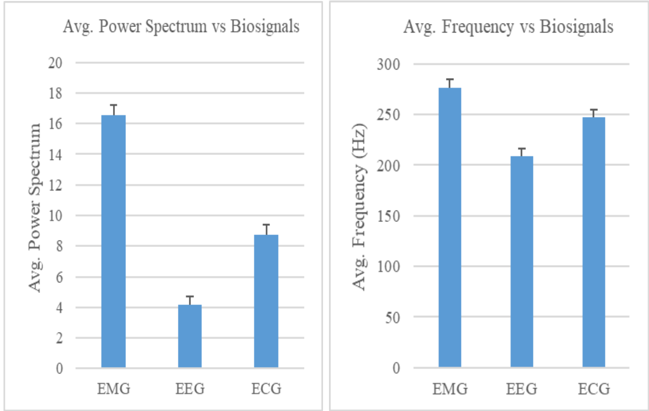

Fig. 12. ECG raw signal of Patient C

The heartbeat rate of Patient C was evaluated by employing Equation (15). Based on the calculation, Patient C with a resting heartbeat rate of 71.29 bpm was categorized as average heartbeat rate level. The average heartbeat rate for 10 patients was 68.09 bpm.

Next, some signal processing steps of heartbeat segmentation, heart rate normalization and LPC application were applied to the raw ECG data. Then, Fast Fourier Transform (FFT) was applied to the resulting data for the calculation of the power spectrum and frequencies.

*D. Average Power Spectrum and Average Frequency*

The average power spectrum and average frequency of biosignals for 10 patients were computed.




(a) (b)

Fig. 13. Graph of average for 10 patients. (a) Average power spectrum, (b) Average frequency.

Fig. 13 showed the average power spectrum and the average frequency of biosignals for 10 patients. The average EMG power spectrum, EEG power spectrum and ECG power spectrum were (16.55 ± 0.67), (4.17 ± 0.52) and (8.76 ± 0.61) respectively. On the other hand, the average EMG frequency, average EEG frequency and average ECG frequency were (276.29 ± 8.14) Hz, (209.16 ± 6.97) Hz and (247.32 ± 7.38) Hz respectively.

*E. Stroke Vector Calculation*

Equation (27) to Equation (34) in Section II Part E were applied to compute for the stroke vector value. After exploring to the EMG, EEG and ECG sensor measurements, the patients were asked to perform the virtual rehabilitation training including 'Pick & Place' and 'Stone Breaker'. Their abilities to carry out the rehabilitation exercise were recorded. These were recorded as the actual patients' result, which were employed to make a comparison with the expected outcome as illustrated in Table I. This was aimed to evaluate the accuracy of stroke vector Equation (34) as predicted by using the machine learning technique. The result of computed stroke vector and the ability of stroke patients to implement the rehabilitation training was presented in Table II.

Table II: Result of stroke vector vs ability to conduct training

| Patient | Stroke Vector | Ability to conduct training |
|---|---|---|
| A | 1.19 | All levels [a] |
| B | 0.88 | Cannot play any |
| C | 1.39 | All levels |
| D | 1.00 | PP [b] (Level 1), SB [c] (Level 1) |
| E | 1.35 | All levels |
| F | 1.00 [d] | PP (Level 1), SB (Level 2) |
| G | 1.47 | All levels |
| H | 0.94 | Cannot play any |
| I | 1.40 | All levels |
| J | 0.95 | PP (Level 1), SB (Cannot) |

Note: [a] All levels = Pick & Place (Level 1-3) and Stone Breaker (Level 1-3). [b] PP = Pick & Place. [c] SB = Stone Breaker. [d] s = 1.02, rounded to 1.

The assessment of their ability to complete the virtual training was done for two games. For instance, the patient could not even stack up 2 blocks in Level 1 of 'Pick & Place' was categorized as inability in completing the game. Besides, the inability to perform 'Stone Breaker' was defined when the patient used up all the three available lives in Level 1. Moreover, the capability of completing all levels meant that the patient was able to stack all the blocks in all levels of 'Pick & Place' and break all the stones in all levels of 'Stone Breaker'. Out of the 10 patients, 5 of them got a stroke vector (s) value of larger than 1, 2 of them obtained a (s) value of equal to 1 and 3 of them acquired a (s) value of smaller than 1. Out of 10 patients, 50% of them possessed excellent stroke condition, 20% of them with moderate stroke condition and 30% of them had a very poor stroke condition. Nevertheless, the average of the stroke vector for 10 patients was 1.157. It signified that recruited patients were averagely in good stroke condition.

### *F. Virtual Rehabilitation Training*

Virtual rehabilitation training of 'Pick & Place' and 'Stone Breaker' were carried out by patients after the biosignals measurement. Time and total cumulative score were selected as stroke recovery indicator for 'Pick & Place' and 'Stone Breaker' respectively. As demonstrated in Table II, there were 3 patients (Patient B, Patient H, and Patient J) with stroke vectors of lower than 1. 3 of them were not able to carry out 'Stone Breaker' whereas Patient B and Patient H were not able to conduct 'Pick & Place'. Table III illustrated the result of conducting the virtual rehabilitation training.

Table III: Result of conducting virtual rehabilitation training

| Patient | Pick & Place (Time, s) | Stone Breaker (Score) |
|---|---|---|
| A | 38 | 26 |
| B | - | - |
| C | 30 | 36 |
| D | 43 | 7 |
| E | 26 | 25 |
| F | 45 | 22 |
| G | 23 | 39 |
| H | - | - |
| I | 30 | 35 |
| J | 55 | - |

In 'Pick & Place', 8 patients were able to complete at least Level 1. The average time taken of 8 patients to stack up 2 blocks in Level 1 was (36.25 ± 10.22) seconds. Patient G used the shortest time of 23 seconds to stack up the blocks, whereas Patient J used the longest time of 55 seconds in the blocks stacking. Out of 10 patients, there were only 7 of them could at least complete Level 1 of 'Stone Breaker'. In 'Stone Breaker', the average total cumulative score obtained by 7 patients was (27.14 ± 10.13). 5 patients (Patient A, C, E, G, and I) completed the game up to Level 3. Patient F managed to achieve Level 2, whereas Patient D was only able to complete Level 1. Patient G acquired the highest total cumulative score of 39, whereas Patient D obtained the lowest score of 7.

### *G. Efficiency for Prediction of Stroke Severity Level*

After the playing of virtual rehabilitation games, the 10 patients were exposed to the upper limb power test, MMSE test and heartbeat rate test. It was aimed to compare the difference between the expected outcome in Table II and the patients' actual performance. The small difference between them revealed that the efficiency of the system in predicting the stroke condition of the patient. The upper limb power test was performed by the medical doctor from the SOCSO Rehabilitation Center Melaka. The limb power was assessed based on the ability of patients to raise their arm. Besides, the MMSE test was performed by asking the MMSE standard questions (employed by most of the physiotherapists) on patients. The heartbeat was measured using the ECG surface sensor.

Overall, all the outcomes showed a satisfying result since most of the actual patients' performance fell within the range of expected result. For instance, Patient C (s = 1.39) showed limb power of 5, MMSE score of 29 and heartbeat rate of 71.29 bpm. All of these criteria fell within the expected range of excellent stroke condition (s > 1). Table IV illustrated the accuracy of the system in predicting the stroke condition.

Table IV: Accuracy of system in predicting stroke condition

| Patient | Actual Result | | | Similarity to Expected Result | Accuracy (%) |
|---|---|---|---|---|---|
| | Limb Power | MMSE | Heart Rate | | |
| A | 3 | 25 | 79.68 | Yes | 100 |
| B | 1 | 13 | 113.81 | Yes | 100 |
| C | 5 | 29 | 71.29 | Yes | 100 |
| D | 2 | 20 | 58.17 | Yes | 100 |
| E | 4 | 27 | 68.53 | Yes | 100 |
| F | 2 | 22 | 57.51 | Yes | 100 |
| G | 5 | 30 | 63.47 | Yes | 100 |
| H | 1 | 16 | 49.43 | Yes | 100 |
| I | 5 | 28 | 71.39 | Yes | 100 |
| J | 2 | 14 | 47.62 | No [a] | 66.67 [b] |

Note: [a] Limb power = 2 (Not satisfied); MMSE = 14 (satisfied); heart rate = 47.62 bpm (satisfied). [b] (2/3)*100% = 66.67%

The average of actual upper limb power was (3.00 ± 1.55), the average actual MMSE score was (22.40 ± 6.05) whereas the average actual heart rate was (68.09 ± 18.01) bpm. Table IV presented that 9 patients got the correct result according to their computed (s) value. Only patient J got a slightly unexpected result. Patient J acquired limb power of 2, MMSE score of 14 and heartbeat rate of 47.62 bpm. Obviously, the limb power of patient J (s < 1) was not in the range of expected result which was supposed to be 1 or 0. However, the overall efficiency of system in predicting the stroke severity level was 96.7% by taking the average of accuracy of 10 patients.

## IV. Discussion

### *A. EMG, EEG and ECG Signal Processing*

Signal processing steps were crucial in removing the unnecessary features of the biosignals. For the EMG signal, the smoothing technique which was sliding RMS was mandatory to filter out extreme values such as huge noise interference. By comparing the magnitude of EMG signal in

Fig. 7 and Fig. 8, the amplitude of raw EMG signal was significantly reduced by applying this technique. Nevertheless, the shape and distance of the burst were still the same as the signal before applying the technique as displayed in Fig. 14. Thus, reducing noise could enhance the EMG signal accuracy.

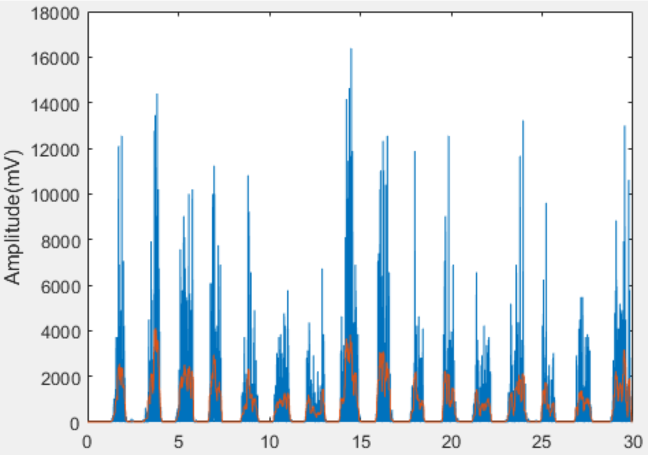


Fig. 14. Effect of applying smoothing technique of EMG.

Besides, filtering of the EEG signal could remove artifacts. Since there were large drifts in the EEG data, a high-pass filter can filter out slow frequencies. For ECG signal, the heartbeat signal appeared to be more stable as demonstrated in Fig. 12. The consistency of the ECG signal was achieved since there was no sudden high or low value. Thus, the preprocessing steps were mandatory in removing the noise so that the resulting ECG signal was not fluctuating.

### *B. Average Power Spectrum and Average Frequency*

There was a noticeable difference between the average EMG power spectrum and the average EEG power spectrum. The average EMG power spectrum was almost four times larger than the EEG power spectrum. The main contribution to the factor was that EMG power was mainly contributed by the muscle contraction, while the contraction resulted in the large electrical signal produced. In this way, the electrical signal created by the muscle contraction was more than the electrical signal generated by the brain. In this case, the patients were required to raise and release their arm for 30 seconds repeatedly. Therefore, the force produced by the arm muscle (especially bicep and deltoid muscles) was significantly large in order to completely raise the arm. The simple arm raising action would not require the large brain functioning led to a smaller average EEG power value.

### *C. Stroke Vector Calculation*

As demonstrated in the ‘Result’ part, the stroke vector Equation (34) had high accuracy in assigning the patients to appropriate virtual training. The result revealed that the ability of 10 patients of performing games (Table II) was closed to the expected condition (shown in Table I). Thus, stroke vector calculation resulted from the machine learning could accurately assign patients to suitable rehabilitation.

Table V: Summary of patients in fulfilling expected result

| Stroke Vector (s) | Patients (Fulfilled) | Patients (Not fulfilled) |
|---|---|---|
| $S > 1$<br>Expected Result [a]:<br>- PP (all levels)<br>- SB (all levels) | A, C, E, G, I | - |
| $S = 1$<br>Expected Result [b]:<br>- PP (Level 1)<br>- SB (Level 1) | D | F |
| $S < 1$<br>Expected Result [c]:<br>- PP (no)<br>- SB (no) | B, H | J |

Note: [a] $S > 1$; limb power $\geq 3$; MMSE $\geq 24$; $60 \leq$ bpm $\leq 100$. [b] $S = 1$; limb power = 2; $18 \leq$ MMSE $\leq 23$; $50 \leq$ bpm $\leq 59$ & $101 \leq$ bpm $\leq 110$. [c] $S < 1$; limb power $< 2$; MMSE $< 18$; bpm $< 50$ & bpm $> 110$.

Table V showed the summary of 10 patients in fulfilling the expected result. All the stroke patients with stroke vector of larger than 1 were capable of completing the virtual rehabilitation games since they had excellent upper limb power of at least 3 and MMSE score of at least 24. In this scenario, the upper limb power of at least 3 was the fundamental requirement to raise and release the impaired arm. According to a professional medical expert, limb power with at least 3 denoted that the patients were able to raise his limb himself against the gravitational force [18]. In this way, both the rehabilitation games needed lifting of the impaired arm. Hence, the 5 patients could complete the game. On the other hand, the MMSE score of at least 24 symbolized that the patients had no cognitive impairment. Moreover, it also implied that the patients owned high concentration and the ability to understand instructions [19]. With that, the patients could differentiate the different sizes of blocks in ‘Pick & Place’ and stacked it in order. Besides, the patients were able to recognize different colors of stones in ‘Stone Breaker’, thus they broke the stones correctly.

Apart from that, there were 2 stroke patients with stroke vector of 1 as displayed in Table V. Patient D fulfilled the expected outcome in which he could only complete Level 1 of both games. Limb power of 2 signified that the patient could hardly raise his impaired limb (against the gravity) [18]. Therefore, Patient D could hardly reflect the moving ball in ‘Stone Breaker’ and stack the blocks in ‘Pick & Place’. Hence, he could only complete Level 1 for both games. Nevertheless, Patient F acquired (s) value of 1.02 but it was rounded off to 1.00. He was expected to perform better than the predicted outcome so that he could complete the ‘Stone Breaker’ up to Level 2. This meant his gripping ability was poor while his upper limb impairment was considered at a moderate level.

As demonstrated in Table V, 3 stroke patients got the (s) value of less than 1. Patient B and Patient H achieved the expected result. They failed to complete any level in both games for the reason of possessing the upper limb power of lower than 2 and MMSE score of less than 18. The result exhibited that they could not even stack any single block in ‘Pick & Place’ and break any stone in ‘Stone Breaker’. This is due to the reason of the limb power of less than 2 meant that there was no muscle contraction or only flicker of muscle contraction. Consequently, weak muscle contraction could not even raise the impaired limb. Besides, the low MMSE score represented severe cognitive impairment. The patients could not even understand the instructions in executing the virtual training. Wrong gameplay action by both patients led to no score.

Patient J was the only one who obtained an unexpected result. The main contributor to this factor was the patient owned large muscle force (EMG signal) but very poor EEG and ECG signal. Hence, the combination of the biosignals resulted in a low stroke vector. However, the large muscle force allowed him to at least complete the ‘Pick & Place’ Level 1. However, he did not understand the gameplay instruction of ‘Stone Breaker’. Instead, he just simply moved the paddle without the intention to catch the moving ball. Overall, most of the patients (n = 8) had successfully achieved the expected outcome. Therefore, the designed framework can effectively assign the patients to suitable virtual training.

### *D. Virtual Rehabilitation Training*

Time and total cumulative score were selected as stroke recovery indicator for ‘Pick & Place’ and ‘Stone Breaker’ respectively. In ‘Pick & Place’, the shorter the time required to stack up the blocks, the better the gripping ability of the patient. Patient G possessed limb power of 5, so he could easily stack up the blocks within a short period. He could complete the blocks stacking without any delay.

On the other hand, Patient J (with weaker limb power of 2) failed to stack the block in the first attempt. In the first attempt, the poor gripping ability caused the unsuccessful stack. Success in blocks stacking was achieved in the second trial. Thus, the total time taken was extended. Besides, Patient F used the second-longest time of 45 seconds in blocks stacking since he had a feeble gripping ability. Slow fingers movement caused he wasted 27 seconds to pick up the first block.

In ‘Stone Breaker’, the higher the total score obtained, the better the moving ability of the impaired arm. 5 patients who could complete up to Level 3 possessed limb power of at least 3. This meant that their impaired arm moving abilities were excellent. Patient G could manage to complete the game up to Level 3 with the total score of 39. This signified that Patient G owned the largest range of motion.

Patient D (with weaker limb power of 2) could only break down 4 stones in Level 1 after he used up all the available lives. The failure of breaking all the stones in Level 1 resulted in a low score of 7. Hence, Patient D’s impaired arm moving ability was poor. Besides, Patient F possessed better limb power compared to Patient D. He could break down 9 stones in Level 2. However, he wasted 2 lives to break the last stone in Level 2 caused him to lose the game in Level 2.

### *E. Efficiency for Prediction of Stroke Severity Level*

Most of the patients (n = 9) acquired a satisfying result. Based on their computed stroke vector value, their limb power, MMSE score and heart rate fell within the expected range. Nevertheless, Patient J obtained an unexpected result (limb power = 2). It was due to the reason of Patient J possessed slightly high upper limb muscle force which induced high EMG electrical signal. In consequence, the slightly high EMG signal had proven that the upper limb power measured at the end of the experimental study was correct. If the impaired limb owned no power, then the upper limb power should be 0 or 1. Besides, the low MMSE score and heart rate implied that the low EEG and ECG signal that were measured at the beginning of the experiment were correct. The low EEG and ECG values induced a low stroke vector value of less than 1.

Overall, the efficiency of the designed framework was high. With the efficiency of 96.67%, it can accurately estimate the stroke condition of the stroke patient. It signifies that the developed system is efficient to predict the stroke severity level. This designed system of combining EMG, EEG and ECG brings a better effect than the traditional method of National Institutes of Health Stroke Scale (NIHSS) on determining the stroke level. The computerized method in this paper brings better performance than NIHSS since NIHSS comprises items with poor reliability and redundancy [10].

## V. CONCLUSION

To summarize it, the assessment on the stroke severity level is essential to determine the stroke condition of the patient. In this paper, stroke severity level of the stroke patients is determined by using the combination of EMG signal, EEG signal and ECG signal. The biosignals are combined for the stroke vector calculation. The stroke vector is employed to assign the patient with the appropriate virtual rehabilitation training, including ‘Pick & Place’ and ‘Stone Breaker’. The result had proven that the calculated stroke vector value could effectively assign the patients to the appropriate virtual rehabilitation training. Overall, the stroke assessment system achieved a high accuracy of 96.67% in determining the stroke severity level of stroke patients. By using the computerized stroke assessment method, it enhances the accuracy in the assessment of stroke severity level. It brings a better stroke assessment effect than the traditional method of NIHSS.

## ACKNOWLEDGEMENT

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