International Journal on Advanced Science Engineering Information Technology

Vol.13 (2023) No. 2
ISSN: 2088-5334

EEG Time-Frequency Domain Analysis for Describing Healthy Subjects and Stroke Patients during Stroke Rehabilitation Motion Tasks

Adhi Dharma Wibawa [a,*], Yuri Pamungkas [b], Monica Pratiwi [c], Rosita Devi Kusumastuti [c], Wardah Rahmatul Islamiyah [d], Diah Risqiwati [c,e]

[a] Medical Technology and Electrical Engineering, Institut Teknologi Sepuluh Nopember, Keputih Sukolilo, Surabaya, 60111, Indonesia
[b] Medical Technology, Institut Teknologi Sepuluh Nopember, Keputih Sukolilo, Surabaya, 60111, Indonesia
[c] Electrical Engineering, Institut Teknologi Sepuluh Nopember, Keputih Sukolilo, Surabaya, 60111, Indonesia
[d] Department of Neurology Airlangga University, Gubeng, Surabaya, 60286, Indonesia
[e] Department of Informatics, Universitas Muhammadiyah Malang, Tlogomas, Malang, 65144, Indonesia

*Corresponding author: *adhiosa@te.its.ac.id*

***Abstract*—To overcome the long-term impact of stroke attacks on society, stroke rehabilitation is the only solution WHO and many healthcare organizations suggested. Until recently, stroke rehabilitation monitoring has been done using visual observation, which has several drawbacks. EEG is a new approach to understanding how the central nervous system controls motion. This study compares the motion pattern done by a group of 12 healthy subjects and nine stroke patients during the rehabilitation motion tasks using the OpenBCI system. Time-frequency domain features, namely PSD, MAV, and STD are used to explore how the patterns differ. Three rehabilitation motions are implemented: grasping, elbow flexion extension, and shoulder flexion-extension. The result shows that the healthy cross-brain correlation happens in healthy subjects. This means that when the left-side arm does the motion, the EEG feature values from the right hemisphere are higher, and vice versa. However, this healthy cross-brain correlation pattern did not happen within the stroke patient group. The overall value of PSD, MAV, and STD from both hemispheres during all motions is higher in the healthy group than in stroke patients. The type of motion also contributes to describing the time-frequency domain feature comparison. In conclusion, this gap value using time-frequency domain features can be used as a target for stroke rehabilitation programs by implementing the EEG technology to monitor it.**

***Keywords*—Stroke rehabilitation monitoring; EEG time-frequency domain; PSD; MAV; STD; home plasticity training; electroencephalogram.**

Manuscript received 4 Sep. 2022; revised 27 Jan. 2023; accepted 3 Mar. 2023. Date of publication 30 Apr. 2023.

I. INTRODUCTION

Stroke has been known as the second biggest cause of death among the world population. Billions of dollars have been spent not only on disease cure and prevention but also on patient rehabilitation. According to the world stroke organization, approximately 13 million people will have a stroke attack every year worldwide, and about 5.5 million people will die due to stroke disease. Many organizations that are concerned about stroke worldwide, such as the Center for Disease Control and Prevention in the United States, have reported that 1 in 6 deaths due to cardiovascular disease was caused by stroke. Every 40 seconds, one person in the United States suffers from a stroke.

These facts have recently dominated discussions among clinicians, doctors, and the government. The only way to reduce the severity of a stroke is to run rehabilitation [1]–[3]. Several nations have developed several guidelines and scaling standards to provide and monitor the rehabilitation of stroke patients, such as Canada, New Zealand, The Netherlands, the United Kingdom, and Australia [4]–[9]. Moreover, several methods have also been made to support the rehabilitation process, such as robotic systems and virtual training [10]–[15]. However, due to the complexity of performing the rehabilitation of stroke patients (because rehabilitation involves not only a physical condition but also psychological, social, economic, and other aspects) [16], [17], several stroke patients reported that rehabilitation did not give any improvement or only give small improvement regarding their motor control [18], [19].

We also discovered that clinicians visually monitor the progression of the rehabilitation process in most techniques for rehabilitating stroke patients. Even though the national standard scale and operation for the stroke rehabilitation program have been implemented, visual observation by clinicians to evaluate rehabilitation progress is subject to many drawbacks and limitations, such as low accuracy, difficulty in precise quantification of progress, fatigue, and other human errors that can blur the evaluation result. EEG (electroencephalography) is a new approach to obtaining the electrical signal from the brain that has been used in several previous studies to evaluate the motor function and other related brain activities of healthy subjects or patients [20].

For example, some previous studies [21]–[23] explored the cortical oscillations behavior related to motor function in the brain. These studies explored motoric functions and post-stroke rehabilitation [24]–[26]. Other studies regarding the use of EEG for exploring the science of human motor control in many fields have also been discussed by Soufineyestani et al. [20]. Since EEG technology can be used to understand the pattern of the human brain's electrical signals in controlling motion, we hypothesized that EEG could also be used to monitor the progressiveness of stroke rehabilitation. In our previous studies, we explored the EEG of stroke patients through time and frequency domain analysis [27]–[29], but the studies were done within one group of stroke patients.

In time-domain analysis, we found that statistical parameters such as Standard Deviation (STD) and Mean Absolute Value (MAV) showed a high potential to be used as a parameter to describe the stroke condition. Another study by Setiawan et al. [28] discovered that PSD (Power Spectral Density) was the best feature for describing the difference between the healthy and affected hands in stroke patients when using frequency domain analysis. However, the study only compared EEG data from the healthy and affected hands of the same stroke patient.

Previous studies have not seen a clear difference in EEG time-frequency domain patterns between healthy subjects and stroke patients. In some previous studies [27]–[29], a higher MAV value of a stroke patient's EEG indicates a better state of brain control. The same rule should apply if this is the case when discussing the PSD value. This means that the higher the PSD value of a stroke patient's EEG, the better the condition of their motor control (or simply healthier). Based on that analysis, in this study, we present the EEG of healthy subjects while performing the same motion tasks given to stroke patients during rehabilitation and compare them with the EEG from stroke patients in time-frequency domain analysis. In the time domain, we compare the healthy and stroke patient groups using MAV and Standard Deviation (STD) values. Meanwhile, we use PSD value in the frequency domain to distinguish between healthy subjects and stroke patients. We also discuss whether we can describe the severity level of stroke using time-frequency domain features (MAV, STD, and PSD), such as low, moderate, and severe stroke conditions. The results of this study will demonstrate the feasibility of using MAV, STD, and PSD as a new approach to monitoring stroke rehabilitation progress.

II. Materials and Method

This study is intended to compare the EEG pattern between healthy subjects and stroke patients using two domains of parameters, namely the time and frequency domain. Twelve healthy subjects are freely participating in this study (5 females, 7 males, age of all genders: 30±5) and 12 stroke patients (age: 50±5.4 years old) who performed the same motion tasks for rehabilitation, such as grasping elbow flexion-extension and shoulder movement/upper limb flexion-extension. All volunteers were fully informed about the purpose of this study and the potential side effects of participating in the EEG measurement. Before participating in this experiment, each participant signed an informed consent form. The EEG of healthy subjects is used as the standard for comparing the EEG of stroke patients. Because we are comparing the severity level through EEG features, clinicians measured the level of stroke severity in the 12 stroke patients using the NIH Stroke Scale (National Institutes of Health Stroke Scale) [7], [30], [31]. These 12 stroke patients came from a public regional hospital in Kediri District, East Java, Indonesia.

Based on their movement conditions, stroke patients can generally be classified into hemiparesis and hemiplegia. These two conditions indicate the severity of the patient's stroke. The patient has difficulty making hand movements (certain body parts) in hemiparesis. Meanwhile, in hemiplegic conditions, stroke patients experience total paralysis because all parts of their bodies are difficult to move. Therefore, a label is needed to determine the stroke severity level. This label consists of low, moderate, and severe stroke conditions. The most relevant forms of labeling are observation and direct measurement from doctors based on the NIHSS score. Table 1 shows the 12 stroke patients in three categories, Low, Moderate, and Severe, based on NIHSS scored by the doctor, including their side of the affected hand. The assessment found 9 of the 12 stroke patients had a stroke that affected their left hand. To reduce the possibility of bias in data analysis, only stroke patients with an affected left hand will be included in the further data processing.

In general, the methodology of this study consists of 4 main steps: data retrieval (EEG recording from all 9 stroke patients), EEG pre-processing, EEG feature extracting (STD, MAV, and Welch's PSD), and EEG features analysis. The EEG features of the healthy and stroke patient groups are compared in the analysis. There is also some discussion about the stroke severity level in those three EEG features during three motion tasks. Fig.1 depicts the flow of all processes.

A. EEG Recording

EEG is an electrical signal produced by the human brain during many activities. EEG wave is in the range 0-50 Hz, with a maximum amplitude of 100 microVolt. EEG has several sub-bands on different frequency ranges [20], [32]. They are Delta (δ), Theta (θ), Alpha (α), Beta (β), and Gamma (γ). This experiment focuses on EEG subbands such as Alpha Low, Alpha High, Beta Low, and Beta High[28]. The UltraCortex Mark IV device (one of the OpenBCI products) was chosen for EEG data recording because it is easier to use and more portable. The sampling rate is 256 Hz.

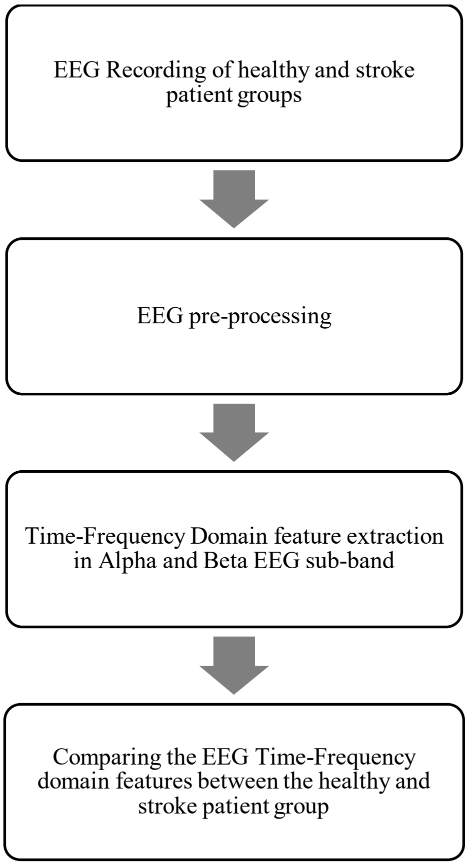

Fig. 1 Methodology

In addition, this device can also capture brain signals within the range of frequency 0 - 50 Hz. Another feature is that it has 16 electrodes installed. Thus, a maximum of 16 channels can be used for EEG recording. The electrodes are also connected to a microcontroller device (Cyton Board) so that the EEG data from the measurement results can be sent to the receiving device (computer) via Bluetooth. The computer on the user's side must also be fitted with a receiving dongle to record and save the EEG data in a *.txt file. The data in this file is a numeric value that represents a human EEG signal.

Although 16 channels can be used for recording EEG data, we only used four channels representing the brain's motor control to compare the EEG between the healthy subjects and the stroke patients. The four channels include F3, F4, C3, and C4. The frontal channels (F3 and F4) are located at the front of the human head, while the Cortex channel (C3 and C4) is the outer part of the cerebrum that plays a role in regulating the body's motor activities (related to the nervous system). Table 1 shows the details of the stroke patient group. Three of the 12 stroke patients were excluded from the study because their affected hand was on the right side. The total number of patients for further analysis in the stroke patient group was nine.

TABLE I
STROKE PATIENT DATA

Patient	**Sex**	**Age**	**Affected Hand**	**NIHSS Score**	**Stroke Severity**
1	Male	52	Left	17	S
2	Male	61	Left	16	S
3	Male	66	Left	15	S
4	Male	48	Left	15	S
5	Male	60	Left	10	MD
6	Male	58	Left	9	MD
7	Female	56	Left	5	L
8	Female	50	Left	3	L
9	Male	58	Left	2	L

*Note: S = Severe; MD = Moderate; L = Low

The NIHSS score ranges from 1 to 24. Stroke patients with low severity have NIHSS scores ranging from 1 to 5, whereas those with moderate severity have NIHSS scores ranging from 6 to 14. Meanwhile, stroke patients with severe conditions are assigned scores ranging from 15 to 24. There are three patients with low severity (L), two with moderate severity (MD), and four with high severity (S) among the nine stroke patients. Every stroke patient has a left affected hand.

The EEG feature of those patients is extracted based on the severity label assigned by doctors. Each patient was asked to perform several hand movements on their affected hand, including grasping (motion one), elbow flexion extension (motion two), and shoulder movement or upper-limb flexion-extension (motion three). Each hand movement is performed for approximately 20 seconds. Therefore, each stroke patient required 60 seconds of EEG recording of the three motion tasks. A timer with an audio marker is applied to remind the patient to change movements from the first to the second and third movements. Of the recorded EEG data for each movement, only about 10 seconds were taken for EEG feature extraction. The overview of cutting the EEG data is shown in Fig. 2.

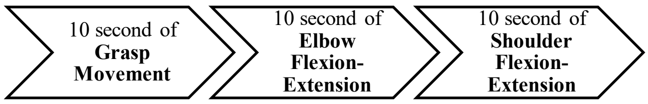

Fig. 2 Data segmentation for the Pre-processing stage

For feature extraction, 10 seconds of EEG data were extracted from each recorded EEG data during one specific motion (the middle portion). The main reason is to ensure that the EEG data accurately represents the motion state and not an intermediate state of changing the motion task.

B. EEG Pre-Processing

The raw EEG data tends to contain noise and artifacts. For this reason, the pre-processing stage aims to clean the EEG signal that has been exposed to artifacts. The pre-processing stages of EEG data consist of bandpass filtering, Automatic Artifact Removal (AAR), Artifact Subspace Reconstruction (ASR), and Independent Component Analysis (ICA). All pre-processing stages are done using Matlab (EEGLab). The EEG bandpass filtering is carried out using an IIR bandpass filter with a frequency range of 0.5 Hz to 45 Hz. The lowpass filter was set to 0.5 Hz because, at that frequency, the signal artifact coming from the muscle tends to be lower than 0.5 Hz [33]. In addition, to avoid artifacts or noise from the electrical signal (50/60 Hz), the high pass filter was set to 45 Hz. During the EEG recording process, the most prominent artifact is the electrical signal frequency.

After performing bandpass filtering for the signal, the next process is artifact cleaning using Automatic Artifact Removal (AAR). The EEG signal is very vulnerable to artifacts in the form of other signals (EOG, EMG, and ECG). In order to separate or eliminate EOG signals (signals arising from the eye muscles), the Blind Source Separation (BSS) method is used. This method is already included in the Automatic Artifact Removal (AAR) process. Not only EOG signals, EMG signals (signals arising from muscle movement), and ECG signals (signals arising from the heart muscle) are also cleared out or separated from EEG signals. Meanwhile, the Independent Component Analysis (ICA) process is an advanced stage of cleaning artifacts in the EEG signal. The ICA process will maintain the main independent components of the signal. These independent components must also describe the EEG signal's characteristics clearly.

C. Time Domain Features Extraction

In this study, statistical parameters such as Mean Absolute Value (MAV) and Standard Deviation (STD) were extracted from the EEG data [27]–[29], [34], [35]. Statistical parameters show the relative amplitude (power) of EEG data. Within 10 seconds duration of EEG data, there will be 10x256 data points. These 2560 data points were then cut into 20 chunks. Each chunk consists of 128 data points. The MAV and STD are then calculated from each chunk. The MAV and STD features are then calculated as the average value of those 20 chunks. Below is the formulation for calculating the Mean Absolute Value (MAV) and Standard Deviation (STD) features.

- Mean Absolute Value:

$$MAV = \frac{\sum_{i=1}^{n} |x_i|}{n} \tag{1}$$

- Standard Deviation:

$$STD = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n-1}} \tag{2}$$

D. Welch's PSD Feature Extraction

In the frequency domain, PSD (Power Spectral Density) is one of the features of the EEG signal for further analysis [28], [33], [36]. PSD represents the power distribution at a certain frequency or frequency range[37]. The calculation of the PSD utilizes Fourier Transform. Meanwhile, Welch's method is a form of approach to calculating the PSD value of an EEG signal. Welch's method has become very popular in calculating PSD values because it can reduce noise in the frequency spectrum compared to conventional PSD or other PSD methods. This study calculated the Welch's PSD feature extraction using Python programming. The following are the formulas for calculating Welch's PSD[37].

$$S_x(v) = \frac{1}{K} \sum_{k=1}^{K} P_k(v) \tag{3}$$

where:
$S_x(v)$ = periodogram value for Welch's PSD

$$P_k(v) = \frac{1}{W} |X_k(v)|^2 \tag{4}$$

where:

$$W = \sum_{m=0}^{M} w^2[m] \tag{5}$$

and, $X_k(v)$ is the DFT for each window

E. Data Presentation

For data analysis, we present the MAV, STD, and PSD values from both groups of healthy subjects and stroke patients when performing the rehabilitation motion tasks such as grasping, elbow flexion-extension, and upper-limb flexion-extension. The features were extracted from 10 seconds of EEG data. The features calculation was obtained from the average of all four EEG sub-bands, namely Alpha High, Alpha Low, Beta High, and Beta Low, and was presented based on the same hemisphere (for example, F4 is presented with C4, and F3 is with C3). The EEG features for the healthy group are presented in two types of motions: the left upper limb and the motion from the right upper-limb, whereas the EEG features for the stroke patients group are extracted from only the left upper limb. Furthermore, we present EEG features from all three types of low, moderate, and severe stroke severity levels to see if our three chosen features can differentiate the stroke severity levels.

III. Results and Discussion

A. PSD Feature

The Power Spectral Density (PSD) from the healthy subjects is used to compare stroke patients' PSD. This result presentation follows how the brain controls the motions [38]. The right hemisphere controls the motion of the left-side upper limb, while the left hemisphere controls the right-side upper limb. When we adopt this concept, we should find that when the left-side arm makes the motion, the PSD value made by the right hemisphere should be higher, and vice versa.

Fig. 3 shows that the right-left hemisphere theory [38] works well in this result. When the right upper limb was moved, the PSD of the left hemisphere was greater than the PSD of the right hemisphere. When the left-side upper limb was moved, the right hemisphere displayed a higher value of averaged-PSD (see Fig. 3). PSD, or Power Spectral Density, represents brain power distribution. PSD is proportional to the amount of electrical activity in the brain.

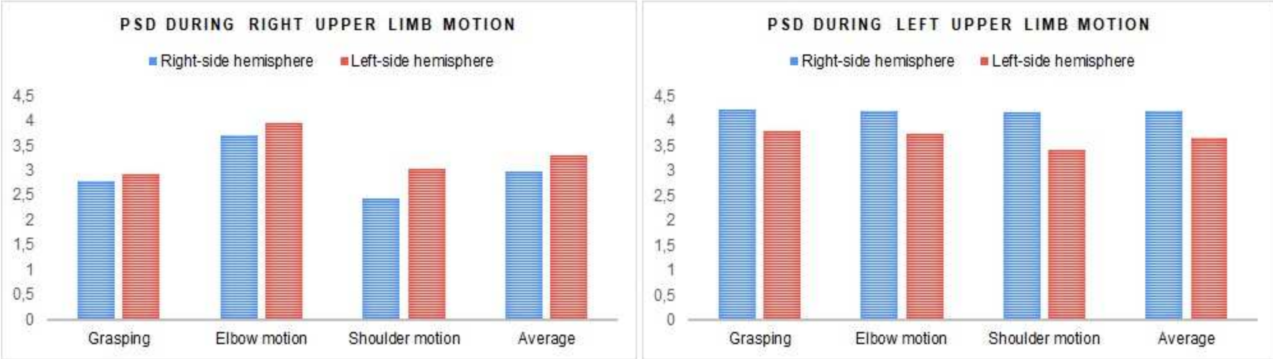

Fig. 3 The PSD value of the healthy subjects in three motion task

Meanwhile, Fig. 4 depicts the PSD value of stroke patients. Fig. 4 shows the PSD only from the right hemisphere because all of the patients' motions were performed by the affected hand, the upper left limb. Fig. 4 shows that stroke patients' movement patterns differ from those of the healthy groups.

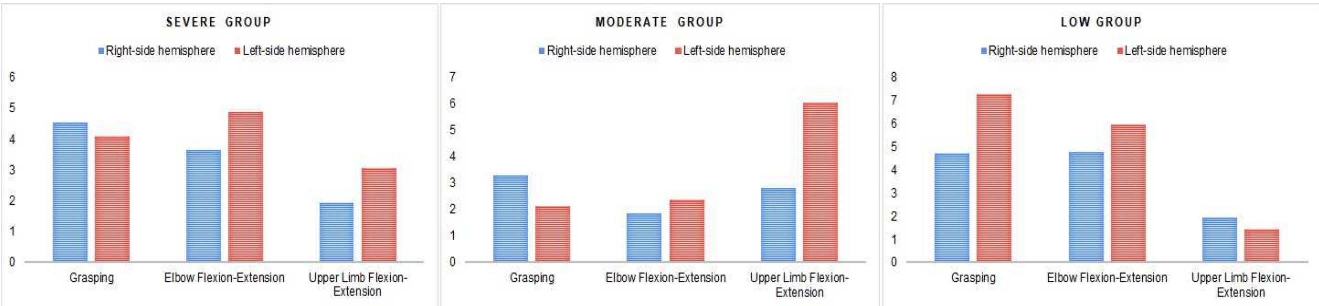

Fig. 4 The PSD value of stroke patients based on the severity level

B. Mean Absolute Value (MAV) and Standard Deviation (STD) Feature

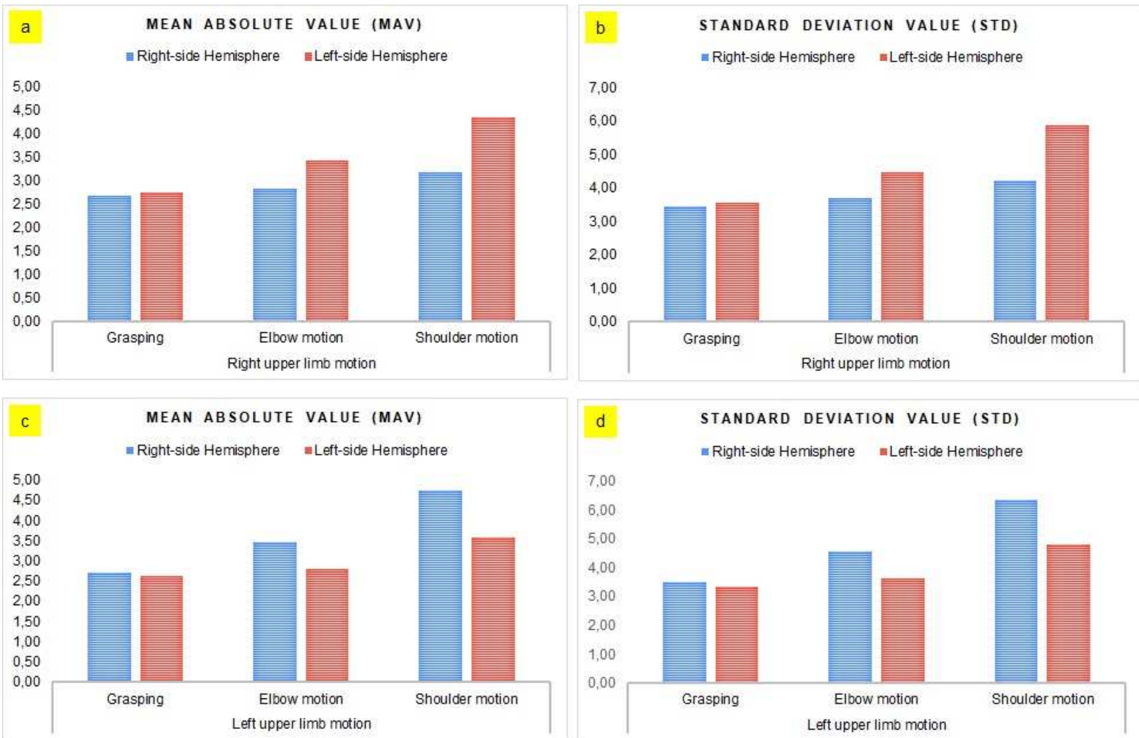

Fig. 5 The average MAV and STD values from all healthy subjects (a-b: the right upper limb motion, c-d: the left upper limb motion)

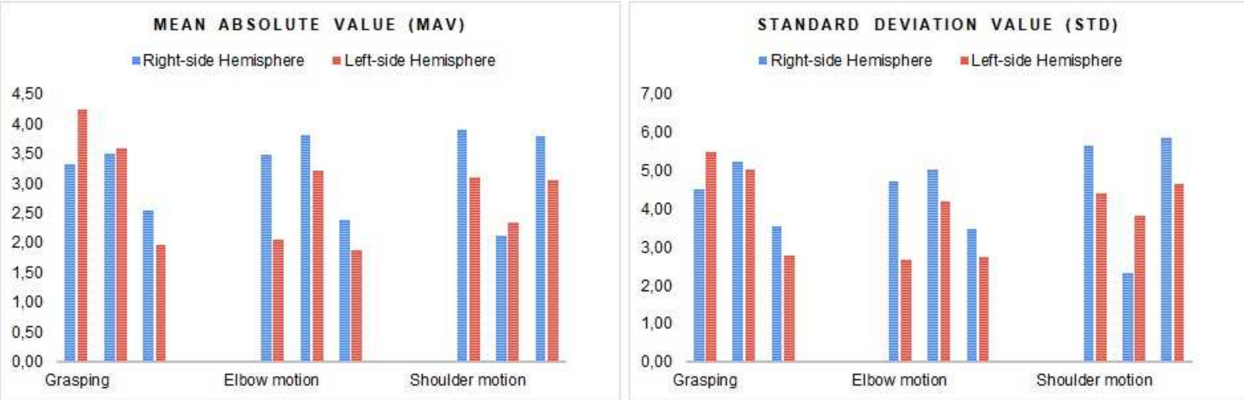

Fig. 6 The average MAV and STD values from all stroke patients in all three motion tasks

Similar to the PSD value, in time-domain features, MAV and STD are also presented in the average value per healthy subject from all 4 EEG sub-bands, and then the mean value of MAV and STD of all healthy subjects was calculated and presented in Fig. 5 based on the hemisphere. Meanwhile, the average MAV and STD values from all stroke patients in all three motion tasks are presented in Fig. 6.

C. Discussion

The results are presented in three ways in this section. The first is a comparison of each PSD, MAV, and STD value per hemisphere between the healthy group and the stroke patients to see how the hemisphere and the sidearm are related. The second is a more general comparison of the PSD, MAV, and STD values between the two groups. The third step is to see if the different stroke severity levels cause a significant difference in PSD, MAV, and STD values, particularly when performing the three different motion tasks.

According to the nature of how the brain should work [32], [38], [39], in this experiment, we use the EEG pattern from the healthy group as a ground truth. When we look at Fig. 3, especially on the average bars, we can see that the PSD value on the right hemisphere is higher when the left arm makes the motion. We call this condition a healthy brain cross-correlation (HBCC). When we compare it to the motion of the right arm, we see a similar HBCC condition. The difference between these two HBCC conditions is the average PSD value produced by each hemisphere. When the motion is performed with the right hand, and the subject is also right-handed, the PSD value from both hemispheres appears to be lower than when the motion is performed with the left-side arm.

This could be explained by healthy subjects requiring less effort to perform the right-side arm motion. Simply put, the brain requires less electrical stimulation. When the left arm makes the motion, when the subjects are right-handed, they will require more attention and effort in the brain to control the motion done by the left arm. This asymmetric condition confirms well with the analysis done by Lukoyanov et al. [40], even though it compared two groups of stroke patients with different brain injury conditions.

Furthermore, the HBCC condition did not occur in the stroke patient group (see Fig. 4). The left arm performs all motions in the stroke patient group, and all stroke patients are right-handed. According to Min et al. [38], the PSD of the right hemisphere (F4 and C4) should be higher than the PSD of the left hemisphere (F3 and C3), but the stroke patients show a different pattern in this experiment. When we compare the overall PSD value between the two groups in all tasks, we can see the result in Fig. 7 below.

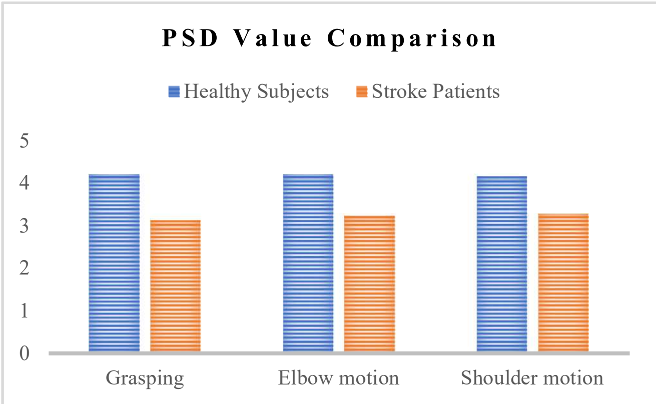

Fig. 7 PSD value comparison from the same hemisphere and the same arm-side between the healthy subject and the stroke patient groups during three motion tasks

Fig. 7 shows that the PSD value from stroke patients in the same hemisphere is generally lower than that of healthy subjects. In the healthy subject group, we discovered that when the left-side arm makes the motion, and the subjects are all right-handed, the brain requires more attention and effort to perform the motion, resulting in a higher PSD value. However, the PSD value from the stroke patient group (from the same hemisphere) appears insufficient (see Fig. 7).

Using MAV and STD features, we can see that the HBCC condition occurs in healthy subjects in time-domain analysis (see Fig. 5). When the left arm performs the motion, the MAV and STD values from the right hemisphere tend to be higher. However, the average value from each hemisphere differs.

However, overall, when we compared the value of MAV and STD from the same hemisphere between the healthy subjects and the stroke patients, we found that the average MAV and STD from the healthy subjects showed a higher value (see Fig. 8). This suggests that the amount of brain electricity activated by stroke patients has decreased as a result of some damage to the patient's brain network [41]. From the standpoint of stroke patient rehabilitation, we believe that this gap value can be used as a target that must be met when stroke patients perform plasticity training or rehabilitation toward the value of the healthy subject.

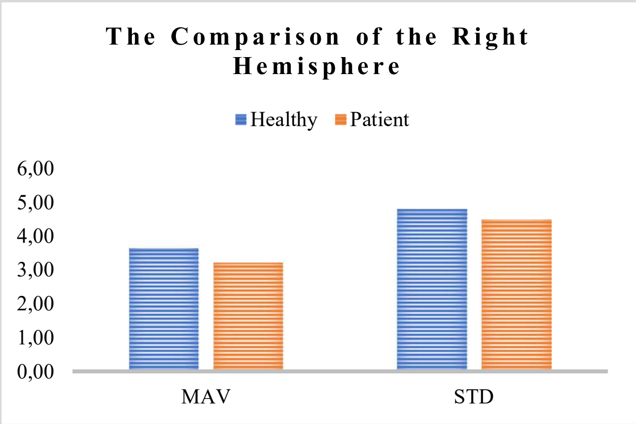

Fig. 8 The comparison of MAV and STD value from the right hemisphere from all motion tasks between the two groups

The type of motion appears to be important as well [39], [42]. When we look at Fig. 4, we can see that with a simpler motion task, the stroke patients show a similar HBCC pattern to the healthy group. We hypothesize that this is because the grasping motion is so simple that the level of difficulty cannot clearly distinguish between the stroke patient group and the healthy group. However, when we examine the shoulder motion task, we can see a significant difference between the two. We could not find clear evidence that stroke severity levels can be differentiated using the PSD, MAV, and STD within the stroke patient group. This result showed that this method of comparing several parameters such as MAV, STD, and PSD between the healthy subjects and the stroke patients has a high potential to be used as a tool for monitoring stroke patients at home. The stroke patients can perform the rehabilitation motion at home, then the EEG system records each parameter during the rehabilitation, and the parameter data are saved to a database. For the next rehabilitation schedule, these two results can then be compared to see the progress of the rehabilitation process. We call this system home plasticity training. In terms of applicability, this system can ease stroke patients in reaching the hospital and avoid them from the traffic jam, stress during the queue line in the hospital, and other difficulties when stroke patients have to go to the hospital.

IV. Conclusion

We can conclude from this experiment that EEG in the healthy group using time-frequency domain analysis (PSD, MAV, and STD) shows that the HBCC condition occurs as described in McManus et al [33]. When the left arm moves, the EEG in the right hemisphere rises, and vice versa when the right arm moves. However, this pattern in the stroke patient group did not occur. PSD, MAV, and STD values from the healthy group are generally higher than those from the stroke patient group. This implies that the electrical signal activated by the brain hemisphere in stroke patients was reduced by brain damage. There is a gap value in PSD, MAV, and STD parameters between the healthy and stroke patient groups, which can be used as a standard for a stroke rehabilitation program. The comparison, however, must be calculated within the same stroke patient. Overall, this study demonstrates the utility of using PSD, MAV, and STD as distinct parameters for monitoring stroke rehabilitation. However, more patients, particularly those with varying severity levels, should be included in future work so that we can gain a better understanding of the severity levels when described using PSD, MAV, and STD.

Acknowledgment

There is no conflict of interest in writing this article. This study is sponsored by Institut Teknologi Sepuluh Nopember (ITS through i-health flagship research scheme 2021.

References

[1] F. Mawase, K. Cherry-Allen, J. Xu, M. Anaya, S. Uehara, and P. Celnik, "Pushing the Rehabilitation Boundaries: Hand Motor Impairment Can Be Reduced in Chronic Stroke," *Neurorehabil. Neural Repair*, vol. 34, no. 8, pp. 733–745, 2020.

[2] G. Lioi *et al.*, "A Multi-Target Motor Imagery Training Using Bimodal EEG-fMRI Neurofeedback: A Pilot Study in Chronic Stroke Patients," *Front. Hum. Neurosci.*, vol. 14, no. February, pp. 1–13, 2020.

[3] D. Kuriakose and Z. Xiao, "IMP para qué es el ictus, tipos y causas. También para datos epidemiológicos y tratamientos.," *Int. J. Mol. Sci.*, vol. 21, no. 20, pp. 1–24, 2020.

[4] E. J. A. Wiegers *et al.*, "Characteristics, management and outcomes of patients with severe traumatic brain injury in Victoria, Australia compared to United Kingdom and Europe: A comparison between two harmonised prospective cohort studies," *Injury*, vol. 52, no. 9, pp. 2576–2587, Sep. 2021.

[5] E. Esposito, G. Shekhtman, and P. Chen, "Prevalence of spatial neglect post-stroke: A systematic review," *Ann. Phys. Rehabil. Med.*, vol. 64, no. 5, p. 101459, 2021.

[6] T. Wijeratne, C. Sales, C. Wijeratne, L. Karimi, and M. Jakovljevic, "Systematic Review of Existing Stroke Guidelines: Case for a Change," *Biomed Res. Int.*, vol. 2022, pp. 1–11, 2022.

[7] J. Yaria *et al.*, "Quality of stroke guidelines in low- and middle-income countries: a systematic review," *Bull. World Health Organ.*, vol. 99, no. 9, pp. 640-652E, Sep. 2021.

[8] E. Mitchell, E. Ahern, S. Saha, G. McGettrick, and D. Trépel, "The Value of Nonpharmacological Interventions for People With an Acquired Brain Injury: A Systematic Review of Economic Evaluations," *Value Health*, 2022.

[9] A. Chye *et al.*, "Repeated Measures of Modified Rankin Scale Scores to Assess Functional Recovery From Stroke: AFFINITY Study Findings.," *J. Am. Heart Assoc.*, vol. 11, no. 16, p. e025425, Aug. 2022.

[10] Y. Zhao, C. Liang, Z. Gu, Y. Zheng, and Q. Wu, "A New Design Scheme for Intelligent Upper Limb Rehabilitation Training Robot," *Int. J. Environ. Res. Public Health*, vol. 17, no. 8, Apr. 2020.

[11] S. Jacob, V. G. Menon, F. Al-Turjman, P. G. Vinoj, and L. Mostarda, "Artificial Muscle Intelligence System with Deep Learning for Post-Stroke Assistance and Rehabilitation," *IEEE Access*, vol. 7, pp. 133463–133473, 2019.

[12] S. Miao, C. Shen, X. Feng, Q. Zhu, M. Shorfuzzaman, and Z. Lv, "Upper Limb Rehabilitation System for Stroke Survivors Based on Multi-Modal Sensors and Machine Learning," *IEEE Access*, vol. 9, pp. 30283–30291, 2021.

[13] F. Covaciu, A. Pisla, and A. E. Iordan, "Development of a virtual reality simulator for an intelligent robotic system used in ankle rehabilitation," *Sensors*, vol. 21, no. 4. pp. 1–17, 2021.

[14] C. C. Huo *et al.*, "Prospects for intelligent rehabilitation techniques to treat motor dysfunction," *Neural Regen. Res.*, vol. 16, no. 2, p. 264, Feb. 2021.

[15] S. Guillén-Climent *et al.*, "A usability study in patients with stroke using MERLIN, a robotic system based on serious games for upper limb rehabilitation in the home setting," *J. Neuroeng. Rehabil.*, vol. 18, no. 1, pp. 1–16, 2021.

[16] I. N. Medvedev, "Place and possibilities of the robotic system Lokomat in the rehabilitation of patients after ischemic stroke," *Biomed. Pharmacol. J.*, vol. 12, no. 1, pp. 131–140, 2019.

[17] F. H. Lin, D. N. Yih, F. M. Shih, and C. M. Chu, "Effect of social support and health education on depression scale scores of chronic stroke patients," *Medicine (Baltimore).*, vol. 98, no. 44, p. e17667, Nov. 2019.

[18] P. Chen *et al.*, “Sleep Monitoring during Acute Stroke Rehabilitation : Toward Automated Measurement Using Multimodal Wireless Sensors,” pp. 1–15, 2022.

[19] M. Battaglia *et al.*, “The Lack of Systemic and Subclinical Side Effects of Botulinum Neurotoxin Type-A in Patients Affected by Post-Stroke Spasticity : A Longitudinal Cohort Study,” 2022.

[20] M. Soufineyestani, D. Dowling, and A. Khan, “Electroencephalography (EEG) technology applications and available devices,” *Appl. Sci.*, vol. 10, no. 21, pp. 1–23, 2020.

[21] L. L. Tan, M. J. Oswald, and R. Kuner, “Neurobiology of brain oscillations in acute and chronic pain,” *Trends Neurosci.*, vol. 44, no. 8, pp. 629–642, 2021.

[22] A. Criscuolo, M. Schwartze, and S. A. Kotz, “Cognition through the lens of a body-brain dynamic system.,” *Trends Neurosci.*, vol. 45, no. 9, pp. 667–677, 2022.

[23] J. C. Peters, J. Reithler, T. A. d. Graaf, T. Schuhmann, R. Goebel, and A. T. Sack, “Concurrent human TMS-EEG-fMRI enables monitoring of oscillatory brain state-dependent gating of cortico-subcortical network activity,” *Commun. Biol.*, vol. 3, no. 1, Dec. 2020.

[24] Y. Gu *et al.*, “brain sciences A Review of Hand Function Rehabilitation Systems Based on Hand Motion Recognition Devices and Artificial Intelligence,” 2022.

[25] W. Gao *et al.*, “brain sciences Application of a Brain – Computer Interface System with Visual and Motor Feedback in Limb and Brain Functional Rehabilitation after Stroke : Case Report,” 2022.

[26] R. Ohta, E. Weiss, M. Mekky, and C. Sano, “Relationship between Dysphagia and Home Discharge among Older Patients Receiving Hospital Rehabilitation in Rural Japan : A Retrospective Cohort Study,” 2022.

[27] M. D. Novitasari, A. D. Wibawa, M. H. Purnomo, W. R. Islamiyah, and A. Fatoni, “Investigating EEG Pattern during Designed-Hand Movement Tasks in Stroke Patients,” *Proc. - 2020 Int. Semin. Intell. Technol. Its Appl. Humanification Reliab. Intell. Syst. ISITIA 2020*, pp. 141–147, 2020.

[28] H. Setiawan, W. R. Islamiyah, A. D. Wibawa, and M. H. Purnomo, “Identifying EEG Parameters to Monitor Stroke Rehabilitation using Individual Analysis,” *Proc. - 2019 Int. Semin. Intell. Technol. Its Appl. ISITIA 2019*, pp. 337–342, 2019.

[29] M. M. Hartanti, A. D. Wibawa, and M. H. Purnomo, “Homecare and Hospital Stroke Therapy Comparison Using EEG Analysis,” *Int. Electron. Symp. 2021 Wirel. Technol. Intell. Syst. Better Hum. Lives, IES 2021 - Proc.*, pp. 179–184, 2021.

[30] M. Koumo, A. Goda, Y. Maki, K. Yokoyama, and T. Yamamoto, “Clinical Items for Geriatric Patients with Post-Stroke at Discharge or Transfer after Rehabilitation Therapy in a Chronic-Phase Hospital : A Retrospective Pilot Study,” 2022.

[31] O. Lennon, A. Crystal, M. Kwan, C. Tierney, A. Gallagher, and S. Murphy, “Perspectives and Experiences of Cardiac Rehabilitation after Stroke — A Qualitative Study,” pp. 1–16, 2022.

[32] T. Böttger, S. Dennhardt, J. Knape, and U. Marotzki, “‘ Back into Life — With a Power Wheelchair ’: Learning from People with Severe Stroke through a Participatory Photovoice Study in a Metropolitan Area in Germany,” 2022.

[33] L. McManus, G. De Vito, and M. M. Lowery, “Analysis and Biophysics of Surface EMG for Physiotherapists and Kinesiologists: Toward a Common Language With Rehabilitation Engineers,” *Front. Neurol.*, vol. 11, no. October, pp. 1–25, 2020.

[34] P. G. Vinoj, S. Jacob, V. G. Menon, S. Rajesh, and M. R. Khosravi, “Brain-controlled adaptive lower limb exoskeleton for rehabilitation of post-stroke paralyzed,” *IEEE Access*, vol. 7, pp. 132628–132648, 2019.

[35] M. Li *et al.*, “An attention-controlled hand exoskeleton for the rehabilitation of finger extension and flexion using a rigid-soft combined mechanism,” *front. Neurorobot.*, vol. 13, no. May, pp. 1–13, 2019.

[36] M. J. Niegil Francis, M. P. Keran, R. Chetan, and B. Niranjana Krupa, “EEG-Controlled Robot Navigation using Hjorth Parameters and Welch-PSD,” *Int. J. Intell. Eng. Syst.*, vol. 14, no. 4, pp. 231–240, 2021.

[37] M. H. Same, G. Gandubert, G. Gleeton, P. Ivanov, and R. Landry, “Simplified welch algorithm for spectrum monitoring,” *Appl. Sci.*, vol. 11, no. 1, pp. 1–23, 2021.

[38] Y. S. Min *et al.*, “Power Spectral Density Analysis of Long-Term Motor Recovery in Patients With Subacute Stroke,” *Neurorehabil. Neural Repair*, vol. 33, no. 1, pp. 38–46, Jan. 2019.

[39] S. G. Russo, “Hemiplegic Upper Extremity Rehabilitation,” *Neurol. Rep.*, vol. 19, no. 1, pp. 17–22, 1995.

[40] N. Lukoyanov *et al.*, “Left-right side-specific endocrine signaling complements neural pathways to mediate acute asymmetric effects of brain injury,” *Elife*, vol. 10, pp. 1–33, 2021.

[41] G. M. G. Bonuzzi *et al.*, “Effects of the brain-damaged side after stroke on the learning of a balance task in a non-immersive virtual reality environment,” *Physiother. Theory Pract.*, vol. 38, no. 1, pp. 28–35, 2022.

[42] R. R. Krishnan, E. Quan, Y. Yeo, and C. J. Lim, “The Impact of Stroke Subtype on Recovery and Functional Outcome after Inpatient Rehabilitation : A Retrospective Analysis of Factors,” 2022.