A New Perspective on Visualising EEG Signal of Post-Stroke Patients

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Abstract. To date, numerous methods have been developed in response to the EEG signal classification of post-stroke patients, among which feature extraction methods are of particular interest. This paper presents a new perspective on the visualisation of the EEG signal of different post-stroke patients in the image representation that can be used to assist in the classification phase. The new perspective for extracting and visualising EEG sub-band features considers the sequential application of power spectral density (PSD) represented in the kernel distribution estimation (KDE) of the PSD manifold. Experiments conducted on 45 post-stroke patients; 14 early, 17 intermediate and 14 advanced patients demonstrated the potential of the proposed perspective to estimate significant parameters under spectral pattern image representation. Visual representation of this new approach shows that the pattern and relationship of post-stroke patients can be clearly visualised. Significant performance can be achieved by classifying post-stroke patients into early-advanced or early intermediate classes as they reach a perfect dissimilarity score, \( r = 1.00 \). In the meantime, the absence of beta or theta in pairs has relatively consistent performance in classifying post-stroke patients using sub-bands, and the combination of the two has shown the worst results among other pairs. This paradigm should be included in the future context of the EEG signal classification of post-stroke classes, which could better explain the importance of image representation while improving the accuracy of the specified network.

1. Introduction
Electroencephalogram (EEG) is the most common spectral-domain of non-invasive biofield instruments [1], which are now available in a miniature design called Mobile EEG [2–4]. Conceptually, all forms of EEG signals are from captured brain neuronal activity via human head skin, where response activity is transmitted over time through attached EEG electrodes to the scalp in the form of spectral-encoding. EEG-based brain-computer interfaces (EEG-BCIs) are designed as a system that essentially serves as a remote control for post-stroke patients to help them engage in the...
environment. Future applications such as EEG-BCIs have been suggested as a robust way to map neuronal activity to post-stroke patient behaviour when integrated into their mirror neuron system (MNS) [5]. However, given the idea proposed for robust but flexible, compact and low-cost EEG-based BCIs, few attempts have been made [6]. This idea calls for more complicated computational spectral analysis and a cumbersome design to provide a highly accurate and reliable medical care system for extreme medical needs [6–8]. A relatively recent tool for robust open source computational software such as MNE [9,10], VisBrain [11] and NeuroPycon [12] has now been attempted to support rapid EEG spectral signal analysis. This software provides a satisfactory solution for the visualisation of spectral-spatial EEG signals. However, when it comes to the diagnosis of post-stroke patient recovery, the rest of the Mobile EEG work is still far from clinical application. The assumption of whether the interpretation of EEG signal features contributes the most to the form of patient-sent feedback is still in a long debate, where the influential features in the signal were beta [13–15] while some critique theta [14]. This paper therefore presents a new perspective on the visualisation of the EEG signal of post-stroke patients as a comprehensive way to evaluate the sub-band features of the signal, where they were most prominent spatially [16], particularly when referring to the post-stroke resting state of the patient. This paper offers a different perspective on the spatial visualisation of the EEG signal PSD manifold via the KDE function to analyse the significance of the sub-band for extensions and improvements in future post-stroke patient stage classification.

2. Related Work
Stroke rehabilitation is a therapeutic process aimed at maximising the physical, psychological and social potential of the patient. Although patients can recover full consciousness from stroke, most of them cannot perform activities of daily living (ADL) with affected limbs [17,18]. Impairment of the limbs significantly limits the level of activity, as well as the social and physical interactions of the post-stroke patient, requiring rehabilitation. Functional recovery of the limbs, whether fully or partially, can be observed after prolonged rehabilitation exercises [19]. There are usually two influential clinical tools for assessing post-stroke patients; first, conventional procedures through questionnaires such as the Barthel Index (BI) [20] or Functional Independence Measure (FIM) [21]; and second, a variety of assistive technologies [22–24], including Mobile EEG [2,25,26].

2.1. Conventional method to diagnose Post-stroke patients
The different sequelae in the limbs with an impact on ADL have been clinically assessed using the conventional available standardized scales [27]. Taking into account the outcomes on these methods, the greatest recovery potential is achieved during the second and fifth months after stroke. In general, there are five stages of post-stroke care settings: medical treatment in hospitals, in-patient rehabilitation, at-home health care, out-patient rehabilitation and self-care after discharge. Receiving timely stroke treatment is important as the stroke signs are identified on an individual. An inpatient rehabilitation facility such as the National Stroke Association of Malaysia (NASAM) is a facility for patients to participate in a minimum of three hours of therapy a day, provided by an organised team of specially trained professionals. During rehabilitation, physiotherapists assist patients in practising and performing simple tasks intensively. The level of tasks differs based on the progress of recovery for each individual patient, mainly into three categories: early, intermediate and advanced. The performances of patients are then clinically assessed using the available standardised scales such as BI [20] and FIM [21] to determine if aforementioned patients are able to move on to the next stage of recovery. However, these scales demonstrate a limited capacity for detecting less-sensitive changes that are nonetheless necessary for measuring outcomes of stroke patients. More importantly, these assessments are often subject to the subjectivity of the physiotherapists. Therefore, a supportive tool of classifying post-stroke patients into recovery stages using effective and reliable technology are beyond the conventional requirements.

2.2. Brainwave Visualization of Post-stroke patients
An alternative to the conventional method, the High-resolution Electroencephalogram (HR-EEG) is a long-term EEG imaging technique that is well used in current clinical practice [5], and the
Quantitative Electroencephalogram (QEEG) is second to HR-EEG. These EEGs are generally incorporated into the Brain-Computer Interfaces (BCI) system for post-stroke rehabilitation studies, i.e. the built-in functional passive-remote-control network used by patients in recovery facilities to better communicate with their environment [5,18,28,29]. EEG is an effective imaging technique that visualises the internal reactions of post-stroke patients through their brain-wave response to engage with the rehabilitation programme and provides the caregivers with a quantitative insight into the progress of the programme [5,30]. The ability of EEG-based BCIs to visualise restored motor control in post-stroke patients has been shown to be effective, especially when combined with a goal-oriented physical therapy protocol [30–32]. To the best of the author's knowledge, the majority of these EEG-based BCIs use spectral rather than spatial patterns to observe the brainwave response, which is why the BCIs system was bulky and often operated in a broad complex setup [6–8]. This design is seen as a key challenge to the successful implementation of the BCI programme in a remote recovery centre. The idea of modelling the EEG signal through miniature EEG devices such as Mobile EEG is feasible [6], as Liu et al. [33,34] have shown that once a low-resolution single-trial signal classification model has been implemented in an optimally biased subspace of spatial and spectral dimensions. Further research is therefore required to model the EEG response to the BCIs via the integrated Mobile EEG, which differs from post-stroke patient stages, where spatial patterns can improve the acquisition of EEG signal via Mobile EEG.

2.3. Motivation for different perspective of EEG signal visualization

Staff-patient interaction at all post-stroke treatment levels is vital to the success of the dedicated recovery programmes at each stage. Clancy et al. [35] examined staff–patient communication in inpatient stroke settings for people with post-stroke aphasia and those who supported them. In order to improve staff-patient experience in addressing the psychosocial needs of stroke survivors and their caregivers, ongoing staff training, provision of aphasia-friendly and a communicatively stimulating ward environments have been proposed. However, Gillespie et al. [36] confirmed that stroke practitioners were commonly engaged in the routine use of non-pharmacological post-stroke emotionalism (PSE) interventions that were not clinically tested, and the efficacy of these methods is still unknown. Recently, Dohl et al. [17] released an updated but quick and effective questionnaire, i.e. health-related quality of life (HrQoL) metrics, as a means of identifying patients in need of post-stroke health care, as well as identifying groups for potential interventions. However, the later attempts that Parker et al. [37] had reviewed on the need for appropriate visual and auditory input for digital simulation to assist staff-patient communication seem to have been overlooked in the whole current digital technological advances. An increased severity of the stroke contributes to increased demand for caregivers services. Unfortunately, having compensated for the extent of the stroke, the involvement of an active caregiver did not encourage further treatment for the stroke survivors [38]. Most caregivers are unsure in their decisions, especially in the absence of specialist doctors. Hence, there is a possibility that the decided uncertain progression of the severity level was based on heuristic measure, which subjectively relied on staff-patient co-operation, caregiver experience and patient trust. Thus, as Parker et al. [37] has recognized, computational visualization for stroke rehabilitation needs to be developed and used to enhance staff-patient engagement and reduced heuristic assessment, thereby providing caregivers with the best combinations of knowledge in the absence of a specialist doctor. Therefore in fact, a quick screening that can envision the degree of post-stroke progression is a critical innovation for solving these problem. Hence, up to this certain application, this research is motivated to assist the caregiver with a rapid interpretation of EEG signal using different perspectives of visualization. Apart from decomposing the complex variant of the EEG signal, which requires higher technical knowledge to decipher the pattern, an alternative to this current study is to transform the signal (spectral) into a form of image (spatial), thus facilitating the patient or caregiver's comprehension of the pattern, thereby enhancing the staff-patient co-operation.

3. Methodology

The EEG measurements were carried out at the National Stroke Association Malaysia (NASAM) Petaling Jaya, Selangor, Malaysia. The post-stroke patients were grouped into three categories based...
on the performance score on two assessment scales: Barthel Index (BI) and Functional Independence Measure (FIM). The three categories are early, intermediate and advanced. Table 1 shows the distribution of subjects who participated in this study. 14 subjects were of the early category, 17 subjects under the intermediate category and 14 subjects in the advanced category, adding up to a total of 45 subjects.

In order to respond to technological advances, this study suggested the use of MobileEEG (i.e. Emotive Insight) during brainwave signal acquisition owing to its light-weight features and the advantages of remote and free-style calibration [3,4] that fit the nature of post-stroke recovery programs [39,40]. In addition, MobileEEGs provides users with a Power Spectral Density (PSD) that is fast to produce [3] but the PSD was random over time and varied in multiple description [4,41–43]. Hence, to aid in the rapid visualization of such arbitrary data, the PSD will be the input of the proposed signal-to-image transformation, where the output is the density of the signal energy distributed in the kernel function, and then visualized in an image form.

Table 1. Distribution of Post-Stroke Subjects

| Category of Post-stroke | Number of Subjects |
|------------------------|--------------------|
| Early                  | 14                 |
| Intermediate           | 17                 |
| Advanced               | 14                 |

- **Raw Signal Extraction**

The Emotive Insight execute PSD via a few built-in existing algorithms, yet still provides user with raw EEG signals sampled at 256 Hz. In general, the captured raw EEG signals ranged from 1 to 20Hz, where the cerebral response to human scalp is transmitted via attached EEG electrodes called channel. It can then be subdivided into four general bandwidths i.e. of delta (δ: 0.5–4.0 Hz), theta (θ: 4.0–8.0 Hz), alpha (α: 8.0–13.0 Hz) and beta (β: 13.0 Hz onwards). To interpret the data space s(i) (n) for the bandwidths, the raw signal r(i) (n) in a channel (i) is subtracted from two reference channels c r1 (n) and c r2 (n) as shown in Equation 1 [16] before bandwidth segmentation. And then, these channels need to be segmented into n s epochs, each of which has a n(i) sample due to the fact that the raw EEG signal is non-stationary response. Thus the division of the raw signal into the epochs of (n) meets the necessity of Fourier windowing in the sense of broad representation of EEG stationary signals. It is well known that the magnitude of raw EEG signal is contaminated with technical and patient-related artifacts, therefore it was standard practice to reject these artifacts either being removed manually through visual inference or time-frequency regression such as linear decomposition and linear reconstruction [16]. This implies that each epoch and each signal that was labeled is handled as Gaussian distribution. So any magnitude greater than 3 times the above-average (μ) standard deviation, δ is omitted and replaced by the random ± |μ + 3δ| mean. After the artifacts were rejected, a 58 Hz band pass filter was used to filter each epoch to ensure a lower signal distortion, so that the filtered signals were optimally flat in amplitude and fairly linear in phase response.

\[
s^{(i)}(n) = r^{(i)}(n) + \frac{c_{r1}(n) + c_{r2}(n)}{2}
\]  

- **Relative Power Band Features**

For multichannel time series of s(i) (n) in the n(i) epochs of (i)th channels, the measured signals is a vector matrix of \( [n_{(i)}^T(t); t = 1, ..., T] \), thus the (i)th channels in period of T second will become the n(i)th epoch, where the Nth number of epochs for a person expressed as the following vector matrix (Equation 2); so that Frobenius inner product on the bandwidth space of all matrices returns the sum of diagonal entries of that vector matrix (Equation 3) for fast signal classification [16] as labeled, L in Equation 4.
To extract the sub-band features from the designated signals, \( S^L \), Welch [14] proposed that \( \{x(n): n = 0, \ldots, N - 1\} \) is the single-channel signal epoch. The PSD calculation may be weighted in the overlapping section where the identified signal is split into overlapping length frames, \( L \). Using the Welch method, the modified periodograms of those windows could be estimated and then those window periodograms averaged as follows; [16] where \( U \) is the normalized factor of the power in the window function, \( w(n) \).

\[
S^{(i)}(n) = \frac{r^{(i)}(n) + c_{r1}(n) + c_{r2}(n)}{2}
\]

\[
\bar{p}(f) = \frac{1}{K} \sum_{i=0}^{K-1} \tilde{p}^i(f)
\]

According to the theory of fast Fourier transform (FFT) [44,45], if the sample frequency is \( f_s \), then the significant length, \( L \) of the half overlapped sliding window, \( w \) is twice of \( f_s \), and the number of window in an epoch is \( T-1 \). So, the number of frequency samples \( n_f \) for each sub-band, \( (f_n = f_s/L) \) is the difference between upper and lower frequency range of that sub-band (Equation 8). Since this study considering 4 sub-bands and 2 frontal channels, for each observation, the total number of relative power band features is 8. Hence, the relative power band features, \( \overline{P}_b^c \) is the averaged power sub-band, \( b \) in the recorded channel \( C \) as represented below; [16]

\[
\overline{P}_b^c = \frac{P_b^c}{\sum_{c\in(i)} P_b^c}
\]

where \( c \in \{(i), \ldots, (i)N\}; (i) \) is number of channels;
\( b \in \{\theta: 0.5 - 4.0; \theta: 4.0 - 8.0; \alpha: 8.0 - 13.0; \beta: 13.0 \text{ Hz}\} \)

- **PSD Visualization**

Zhang [16] found out that the distance between two standard matrices measured along the PSD manifold surface gave the captured EEG signal a better perspective of energy behavior. For this analysis, instead of transforming \( \overline{P}_b^c \) into a complex PSD matrix, the kernel function (KDE as in Equation 10) makes it possible to represent the manifold of such relative power-bands in terms of energy density. Throughout this analysis, one will get a first insight at what could be visualized as the pattern of such a relative PSD manifold. It is to be inferred from the study carried out by previous researchers [46–49], that the KDE of the relative power bands of identified patients is distributed in unique distinctive energy pattern. Therefore, the
multivariate probability distribution function, $f_k(x)$ of each relative PSD in a subject can be represented as the following:

$$f_k(x) = \frac{1}{N} \sum_{i=1}^{N} \prod_{d=1}^{D} \frac{1}{h_d} k \left( \frac{x_d - X_{i,d}}{h_d} \right)$$  \hspace{1cm} (9)$$

where $N$ is the number of epochs in a relative sub-band, $D$ as the spatial dimension of $N$, $x_d$ is the PSD of the $d^{th}$ dimension, $X_{i,d}$ is the $i^{th}$ location in the $d^{th}$ dimension, and $h_d$ bandwidth for the $d^{th}$ dimension.

- **Image Analysis**

  The Enhanced Region-specific Algorithm (ERS) as introduced by Razak et al. [50] is used in this study to calculate the formed image intensity and its similarity.

4. **Result and Discussion**

A total of 45 confirmed post-stroke patients (14 Early encoded as ‘E’, 17 Intermediate encoded as ‘I’ and 14 Advance encoded as ‘A’) had been screened for 5 minutes in a resting conditions using MobileEEG. From the raw signals of each patient, we calculate the band-power of the two frontal electrodes that are relative to each other and the relative band-power a signal are 8 in total, indicating four left (delta $\delta_l$, theta $\theta_l$, alpha $\alpha_l$, beta $\beta_l$) and four right (delta $\delta_r$, theta $\theta_r$, alpha $\alpha_r$, beta $\beta_r$) hemispheres. The estimated spatial dimension of the image is therefore the relative relationship between the left and the right sub-bands of the front hemisphere. As a result, the PSD of the four sub-band signals was visualized in an image configuration as shown in Figure 1. Visually, from the images, we could quickly grasp the pattern of the PSD manifolds being distributed and its relationship to the level of the post-stroke patient.

![Figure 1](image.png)

**Figure 1.** PSD of EEG signal in form of KDE image.

Visually, by comparing the images of the early stage to the other two stages, i.e. Intermediate and Advance, based on the size of the spread of the contour; the early stage visualized smaller blob in size
with PSD response intensity, which was locally distributed in a small area (focal spatial range), indicating a smaller variance and a standard deviation between the spatial response. Moreover, between Intermediate and Advance images, only delta and alpha sub-bands give distinctive differences where their PSD response intensities from the intermediate images tend to spread in a wide area and lots of random blobs distributed outside the focal spatial range. This observation indicates that theta and beta sub-bands have not been significant enough to distinguish the PSD response of Intermediate and Advance post-stroke patients, and that the combination of delta and alpha sub-band images is the best combination to classify post-stroke patterns in these three stages. This observation is in good agreement with the findings of other researchers [13–15,51–54], delta and alpha are the best sub-band index for the classification of post-stroke score. Although theta was critiqued as an unreliable measure [14] and beta was considered the least reliable sub-band [13–15]. According to Aminov et al. [52], to date there have been no reported correlations between beta activity and cognitive or functional post-accident outcomes.

By applying the ERS algorithm [50] with linear regression analysis [55–57], this study provides statistical observations of the relationship between the post-stroke stages and the pattern dissimilarity between the imaged sub-band response as shown in Figure 2. The result shows that; (i) 1°, through Figure 2(a), the differences between Early-Intermediate (E-I) and Early-Advance images for all sub-bands except beta were almost 100%, but between Intermediate-Advance images only theta achieved scores above 99% on average. This means that beta images at all stages have a higher similarity. This

![Figure 2](image-url)

**Figure 2.** Relation of the dissimilarity of stage-to-stage pairs (a) together with their linear regression and the Pearson coefficients (b).
also indicates that beta sub-bands are confirmed as non-significant features for the differentiation of post-stroke patients; (ii) 2nd, by linear-regressing the dissimilarity scores in Figure 2(a), the projected Pearson product-moment correlation, r as shown in Figure 2(b) indicates that all sub-band images were different in positive relation between stages, where a comparison of the pattern between Early-to-Intermediate and Early-to-Advanced was shown as the perfect positive correlation.

In spite of the stages, Figure 3 is, on the other hand, the extension regression analysis of the relationship between all sub-band images. The dissimilarity score between all images records a perfect positive relationship if and only if the beta and theta are out of the combination. Once beta and theta were compared together, their similarity was among the highest (r = 0.15). The results in Figures 2 and 3 therefore confirm that beta is the least reliable sub-band where theta is the most reliable feature for the differentiation of post-stroke patients. In addition, the images proposed in this study are confirmed as a definitive method for visualizing the PSD manifolds of the EEG signals and are therefore valid as a new perspective for visualizing the EEG Post-Stroke Patient Signal.

![Figure 3. Relation of the dissimilarity of band-to-band pairs together with their Pearson coefficients.](image)

The following statement can be inferred by combining results between Figure 2 and Figure 3;

- **Insignificance of beta**
  The beta sub-band is often associated with muscle contractions that happen in isotonic movements and are suppressed prior to and during movement changes [58]. This could explain the low level of dissimilarity of beta PSD because of the nature of data acquisition carried out on the post-stroke subjects, where they are instructed to either sit or lay down throughout the EEG recording session. A resting-state EEG reading, since no movement is required, would yield similar levels of beta intensity throughout all three categories of post-stroke patients.
Low dissimilarity score between intermediate and advanced categories

In theory, the EEG readings of post-stroke patients across all three categories should be different. However, the low level of dissimilarity between intermediate and advanced group poses some questions. First of all, it is important to know that the post-stroke patients are categorised into the three recovery groups early, intermediate and advanced by professional physiotherapists at NASAM using performance scores from standardised assessment tools: Barthel Index (BI) and Functional Independence Measure (FIM). The similarity of EEG sub-band values between the intermediate and advanced group shows possibility of inaccurate assessment and classification. This could be caused by the insensitivity of the standardised assessment tools and the subjectivity of physiotherapists, among other possible factors.

5. Conclusion

In this work, a new approach for visualisation of EEG signals has been presented, based on sequential application of power spectral density (PSD) feature extraction and visualization of the kernel distribution estimation (KDE) of the PSD manifold. The results obtained from this method have illustrated significant EEG information of different post-stroke patients for easier classification. Compared to the information obtained from conventional signals of EEG, conveying such data in the form of images has more impact. EEG visuals improve the clarity of information. At first glance of the PSD manifold in form of KDE images for each sub-bands, it can be clearly observed that there is a difference in intensity among the three categories of post-stroke patients. It would be a more difficult task to confirm this inference if only the PSD numbers are presented. Secondly, image analysis can set clear assumptions on potential classification works. From the analysis in Figure 2, a better performance of classifying post-stroke patients into early and advanced or early and intermediate categories can be expected due to their perfect dissimilarity score (r=1.00), while in Figure 3, classifying post-stroke patients using the sub-bands (excluding either beta or theta) are preferred. This can prove to be beneficial as it would replace the traditional trial-and-error method of choosing data inputs for neural network training. In short, the proposed EEG visualisation technique can be applied for multi-class classification problems. The results obtained are promising, as compared to current scientific standards. For further improvement, further exploration is strongly recommended to advance the results beyond the preliminary outcome presented in this paper.

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