Index for Assessment of EEG Signal in Ischemic Stroke Patients

R. Geetha and E. Priya

Abstract Stroke is an acute condition of sudden compromise in vascular perfusion of brain and manifestation of neurological deficit. Worldwide, stroke is the second leading cause of death and also the third leading cause of morbidity and disability. Electroencephalogram (EEG) is a noninvasive method that captures the electrical activity of brain as a signal from the scalp. Detection and reduction of artifacts play an important task to acquire clean EEG signals so as to examine and detect brain activities. In this work, EEG signals from normal and subjects with acute ischemic stroke (AIS) are acquired under standard signal acquisition protocol from public database. The quality of the signal is improved by the techniques. An attempt has been made to detach artifacts by independent component analysis. The preprocessed EEG signal is decomposed by discrete wavelet transform method into wavelet coefficients to reduce the signal dimension. The decomposed signal is categorized as the sub-waves namely alpha, beta, delta, theta and gamma. The index such as delta–alpha ratio (DAR), delta–theta to alpha–beta ratio (DTABR), brain symmetry index (BSI) obtained by Welch's method helps to distinguish AIS from controlled subject. Also, the performance of the procedure is evaluated by statistical measures such as skewness, kurtosis, entropy, mean and variance. It is observed from the results that AIS patients have a high DAR, DTABR and BSI. Results also demonstrate that the extracted statistical metrics are high for AIS compared to that of normal individuals. Thus, the index and statistical metrics used in this work are significant in classifying AIS from normal subjects.

Keywords Acute ischemic stroke · Discrete wavelet transform · Delta–alpha ratio · Delta–theta to alpha–beta ratio · Brain symmetry index

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1 Introduction

Globally, brain stroke is the significant and foremost cause of mortality as well as long-lasting disability. Ischemic stroke is the most common type and has a global prevalence of approximately 11.6 million new cases per year. Among various etiologies, acute ischemic stroke (AIS) is one of the significant causes of morbidity. Around 87% of all strokes are ischemic stroke that is due to the blockage of oxygen-rich blood flow through the brain vessels [1]. Brain function is monitored by electroencephalography (EEG) signals particularly in intensive care unit. Brain ischemia is detected with respect to the characteristics changes that take place in EEG. The feature changes in EEG are correlated with cerebral blood flow and brain metabolism [2, 3].

The feature extraction of EEG signal is done in wavelet transformed domain and feed-forward neural network with extreme learning machine algorithm to demarcate normal and ischemic stroke signals [4]. The characteristics of brain wave are analyzed by different categories of stroke level using relative power ratio [5]. Augmentation in delta power (1–4 Hz) is one of the main features found to be related to ischemic stroke [6]. Delta to alpha power ratio (DAR) demonstrates maximal accuracy in differentiating AIS patients from controls [7]. The prediction of stroke outcome is identified by using neurophysiological markers such as delta–theta to alpha–beta ratio (DTABR) and alpha relative power. The functional outcome of stroke is also determined by measuring the symmetry index, absolute and relative frequency band indices and dynamic time change captured from quantitative electroencephalography (QEEG) [8]. Acute ischemic hemispheric stroke is monitored by continuous bedside monitoring of quantified EEG to measure brain symmetry index (BSI). This measure is consequently correlated with National Institute of Health Stroke Scale (NIHSS) [9, 10]. Among various EEG-derived parameters, BSI is one of the most accepted parameters which is used in the research field for the prediction of stroke prognosis [11].

In this work, an attempt is made to analyze EEG signals automatically by extracting features using wavelet transformation. The ischemic stroke patients from normal subjects are thus distinguished based on indices such as DAR, DTABR and BSI. The performance evaluation of the preprocessing procedure is done by statistical measures such as skewness, kurtosis, entropy, mean and variance.

2 Methodology

2.1 EEG Dataset

The EEG signals are obtained from public open-source repository for open data (RepOD), BNCI Horizon 2020 and the Temple University Hospital EEG Corpus (TUH-EEG) datasets. In these datasets, the EEG signal is recorded for 10 min from each patient using the standard 10–20 EEG electrode placement system (Fig. 1).

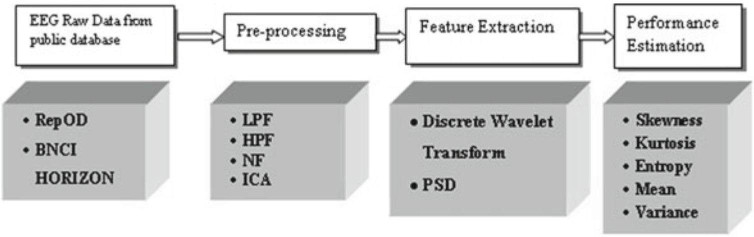


Fig. 1 Block diagram of the proposed approach

The raw ischemic stroke EEG signals from 16 channels comprise all prominent regions of human brain. The acquired signal is sampled at a rate of 250 Hz. These signals are preprocessed, to acquire useful information. Features from preprocessed signals are extracted and compared with normal EEG signals.

2.2 Preprocessing

The spatial information will get lost due to noise and artifacts while recoding the EEG signals from the scalp. The brain signals are filtered by using 30 Hz low-pass filter (LPF), 70 Hz high-pass filter (HPF) and 50 Hz Notch filter. The artifacts are aimed to be removed by independent component analysis (ICA) using EEGLAB.

2.3 Feature Extraction

The preprocessed EEG signal data from the EEGLAB in European data format (.edf) are converted into ASCII data. Then, using Matlab script, the wavelet transformation is done. Wavelet transform estimates spectral information which is expressed as an infinite series of wavelets. The signal is decomposed to a set of coefficients called wavelet coefficients. Adequate numbers of coefficients are computed to reconstruct the signal back. The wavelet transform of a signal is defined as

$$W_{\psi}x(s,\tau) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t)\psi * \left(\frac{t-\tau}{s}\right) dt \tag{1}$$

where $\psi(t)$ is a mother wavelet, s and τ are the scaling parameters, s denotes the oscillatory frequency representing the length of the wavelet, τ indicates its shifting position, and the asterisk denotes complex conjugate.

Discrete wavelet transform (DWT) provides significant information which enables the signal to be analyzed and to decompose into different frequency bands by consecutive high-pass and low-pass filtering of the signal. DWT utilizes scaling and wavelet functions. The smoothing feature of the Daubechies wavelet of order 8 (db8) is used to detect changes in EEG signals. The signal dimension is reduced using db8. DWT decomposition can be expressed as

$$M_{(a)}(b) = x(a) * \varphi_{a,b}(c) \tag{2}$$

$$N_{(a)}(b) = x(a) * \psi_{a,b}(c) \tag{3}$$

where $M_{(a)}(b)$ and $N_{(a)}(b)$ are the approximate coefficients and detailed coefficients resolution of a with c is the time sequence.

The normalized wavelet and scale basis function of $\varphi_{a,b}(c)$, $\psi_{a,b}(c)$ are represented as

$$\varphi_{a,b}(c) = 2^{a/2}\, g_a\left(c - 2^a b\right) \tag{4}$$

$$\psi_{a,b}(c) = 2^{a/2}\, h_a\left(c - 2^a b\right) \tag{5}$$

where $2^{a/2}$ specifies the inner product normalization, a and b are the scaling and translation parameter [11–13].

One of the most common features to analyze the EEG signal is power spectral density. The spectral power density of each channel is computed from the decomposed EEG signal into four sub-waves based on the signal frequency range of alpha (8–12 Hz), beta (14–20 Hz), theta (4–7 Hz) and delta (1–4 Hz) [6]. The calculation of power spectral ratios such as DAR and DTABR is defined as

$$\text{DAR} = \frac{\text{Relative Power Ratio Delta}}{\text{Relative Power Ratio Alpha}} \tag{6}$$

$$\text{DTABR} = \frac{\text{Relative power Ratio Delta} + \text{Theta}}{\text{Relative Power Ratio Alpha} + \text{Beta}}. \tag{7}$$

The degree of symmetry between left and right brain activities is measured using BSI, which is defined as the arithmetic average of absolute value of difference in mean hemispheric power. The BSI determines the amount of ischemic damage in brain. The value of BSI is nearer to 0 which represents perfectly symmetrical and it has higher value closer to 1 that symbolizes the maximal asymmetrical wave. It estimates the overall asymmetry within the identical channels and computes the average of frequency ranging from 1 to 25 Hz. It is defined as

$$BSI = \frac{1}{PO}\sum_{l=1}^{O}\left\|\sum_{k=1}^{P}\frac{RIH_{kl} - LEH_{kl}}{RIH_{kl} + LEH_{kl}}\right\| \tag{8}$$

where RIH_{kl} and LEH_{kl} represent the power spectral density of the left and right hemisphere, O refers to the overall number of Fourier coefficients and P is the total number of electrode pairs [9].

2.4 Performance Estimation

The performance of the procedure is evaluated by statistical measures such as skewness, kurtosis, entropy, mean and variance. These metrics are helpful in distinguishing ischemic stroke patients from normal [14].

3 Results and Discussion

Typical representation of Fig. 2 shows the extracted beta, alpha, theta and delta waveform of EEG spectra for normal individuals and AIS patients. The frequency variation in the EEG spectra noticeable from the figure represents brain function too.

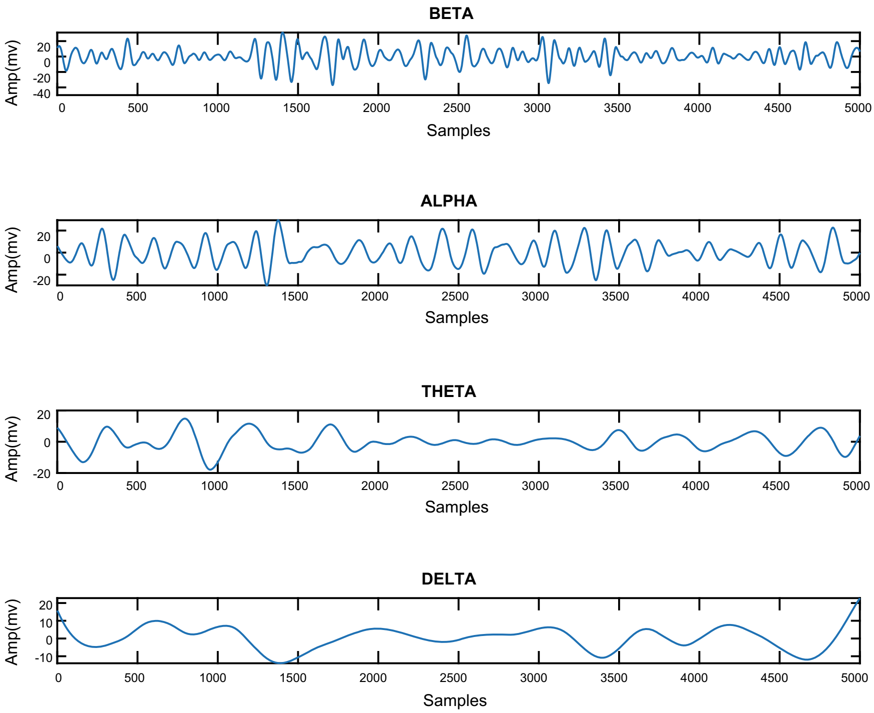
Decomposition of EEG signal using DWT provides the relative power ratio of different frequency segments such that of beta, alpha, theta and delta waves. Relative power indices for all these frequency bands are derived by using absolute value of power from each of the bands as a percent of absolute power summed over the five frequency bands. The comparison of relative power for all frequency bands of AIS patient and normal individual is presented in Fig. 3a–d.

In this scattered graph, the even number of electrodes determines the right hemisphere while the odd number of electrodes represents the left hemisphere. The delta activities of both cerebral hemispheres are high in AIS patient than normal individual as shown in Fig. 3a. The changes in delta activity demonstrate the strong correlation with cerebral blood flow (CBF) and electrical activity of cortical neurons during ischemia. The activities of theta on right and left hemisphere are highly elevated in AIS patients which represents reduction in the brain metabolism than normal individual as shown in Fig. 3b. The relative band power of beta and alpha as shown in Fig. 3c and d tends to be lower when compared with relative band power of delta and theta as shown in Fig. 3a and b. So it is inferred that the beta and alpha components of EEG do not contribute much on assessing the AIS patient condition.

The comparison of normalized average values of band power ratio for AIS patient and normal individual is shown in Fig. 4a. Similarly, the normalized average values of BSI for AIS patient and normal individual are shown in Fig. 4b.

The overlay graph as shown in Fig. 4a represents the average values of band power ratio for AIS patient and normal individual. EEG parameters such as DAR and DTABR value of AIS patient are found to be higher than normal individual. The higher value of DAR and DTABR implies a significant reduction in CBF in AIS patient. BSI is a measure used to find out the symmetry of brain waves between left and right hemisphere. The average values of BSI of AIS patient tend to be higher compared to that of normal individual as shown in Fig. 4b. An average value of BSI nearer to 1 signifies the maximal asymmetry that occurs due to cerebral hypo-perfusion in AIS patients.

The overlay graph as shown in Fig. 5 represents the variations in normalized average values for AIS patient and normal individual. The performance evaluation of the statistical features extracted from the EEG signals such as skewness, kurtosis, entropy, mean and variance of AIS is high compared to that of normal individual. The extracted EEG signals are precised by means of higher-order moments such as skewness and kurtosis. The lack of symmetry or the asymmetry of intrinsic brain activity is deliberated by skewness. A higher-level statistic kurtosis provides the measure of spikiness of EEG signals and is increased relatively to a smaller extent. An increment in the entropy reflects the slowing in the brain activity following



(a)

Fig. 2 Representation of beta, alpha, theta, delta wave of EEG signals for **a** normal individual and **b** AIS patient

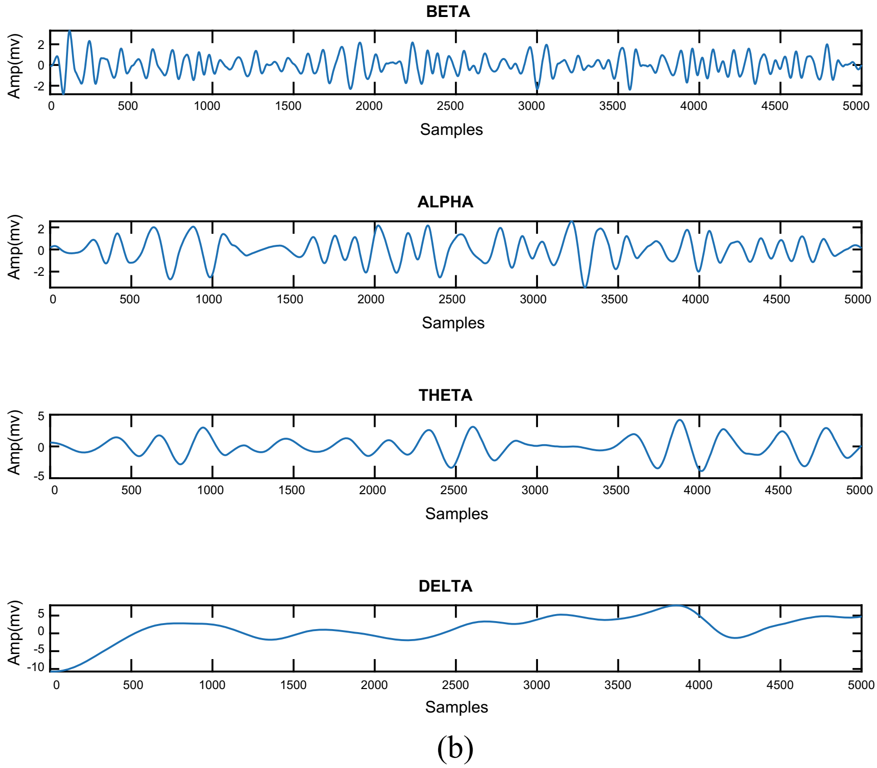


Fig. 2 (continued)

cerebral stroke. The mean and the variance were selected to measure the changes in EEG waves and are used to reveal the cortical involvement in the injured cerebral hemisphere.

4 Conclusion

Assessment of EEG signal helps in distinguishing acute ischemic stroke from the controlled subjects. In this work, appropriate indices and metrics are used as a promising tool to detect acute ischemic stroke lesion**.** The EEG signal obtained from the public database is preprocessed using a combination of low-pass, high-pass filter and a notch filter to eliminate the noise and artifacts. The decomposition of EEG signals is done by using DWT with Daubechies wavelet level 8 as a mother wavelet. The level 8 is categorized into four sub-waves namely beta, alpha, theta and delta. The feature index such as DAR and DTABR is extracted from each sub-waves. The extracted features are further correlated with normal individual. It is observed from

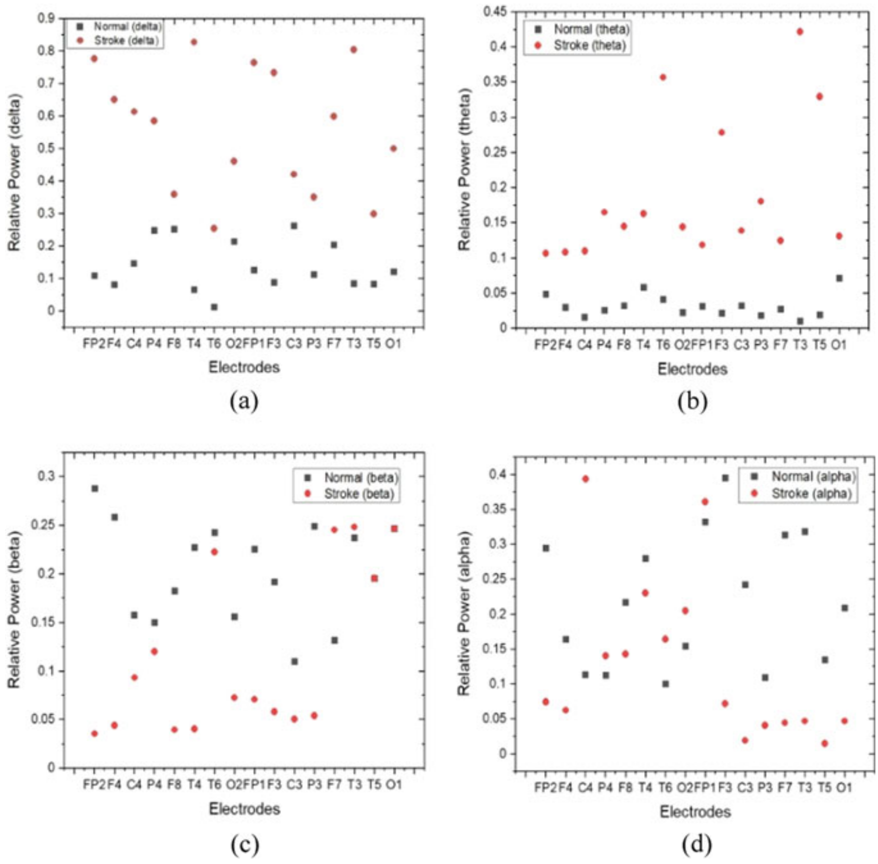


Fig. 3 Comparison of relative power of **a** delta, **b** theta, **c** beta and **d** alpha between normal individual and AIS patient

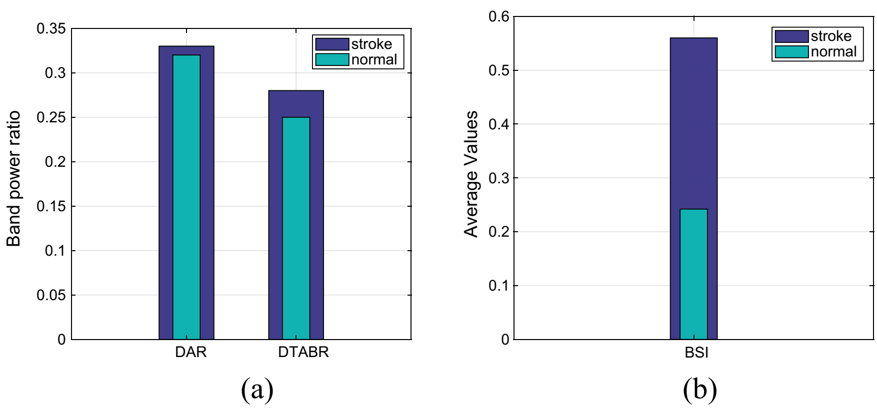


Fig. 4 Average values of **a** band power ratio and b BSI for stroke patient and normal individual

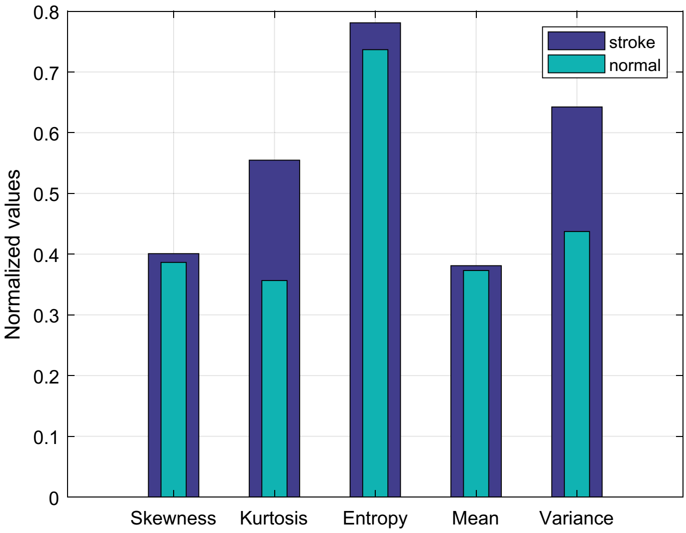


Fig. 5 Variations in normalized average values between normal and stroke patient

the results that AIS patients have high DAR, DTABR, BSI and statistical metrics**.** This higher value of the extracted features signifies severe cerebral infarction which helps in demarcating AIS from controlled subjects.

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