Feature Extraction of EEG Signals Using Variational Mode Decomposition

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***Abstract*:** Epilepsy is one of the most widely recognized a neurological issue of the cerebrum that influence a large number of the world's population. It is characterized by recurrent seizures, which are physical responses to abrupt, typically short, extreme electrical releases in a group of brain cells. Thus seizure identification has extraordinary significance in clinical treatment of epileptic patients. Electroencephalogram (EEG) is most normally used in epilepsy discovery since it incorporates valuable physiological data of the brain. In any case, it could be a test to identify the inconspicuous yet basic changes incorporated into EEG signals. Feature exatraction of EEG signal is center inconvenience on EEG-based brain mapping examination. This paper will extract forty four features from EEG signal in view of variataional mode decomposition (VMD) for epilepsy detection. These various features will assist the classifiers with achieving a decent accuracy when use to arrange EEG signal to distinguish epilepsy. Subsequently, the results have illustrated that VMD has been adopted to extract various features.

***Index terms* - Electroencephalogram, Variational Mode Decomposition, Epilepsy.**

I. INTRODUCTION

Epilepsy is a neurological issue (any confusion of sensory system). The reason for most cases, epilepsy happen because of mind damage, strokes or unusual movement of brain cell (i.e., produce multiple times bigger sign than of ordinary). It causes seizures, loss of mindfulness here and there or neuronal movement in the cortex of the cerebrum. Most of epileptic cases are expanding over the world amazingly every now and then [1].

In general, epileptic issue or seizures are controllable with drug (hostile to epileptic) in about 70% of cases or some of the time with medical procedure or neuron stimulation. The greater part of the individuals with epilepsy can be without seizure with hostile to seizure medicine. Not every one of the instances of epilepsy are long lasting and numerous individuals improve to the point of treatment. Epilepsy is difficult to analyze and troublesome in finding the confusion [2].

Epilepsy can be regularly affirmed with an electroencephalogram (EEG). It is technique for checking and recording electrical movement of the brain. During the test cathodes are set along the scalp. The typical example of brain waves will be changed, notwithstanding when an individual isn't having a seizure however an epilepsy. It is conceivable to analyse epileptic seizure by assessment of the recorded sign utilizing effective procedures [3]. The fig. 1 (https://www.brainlatam.com/products/eeg-electrode-caps) shows the EEG electrode placement

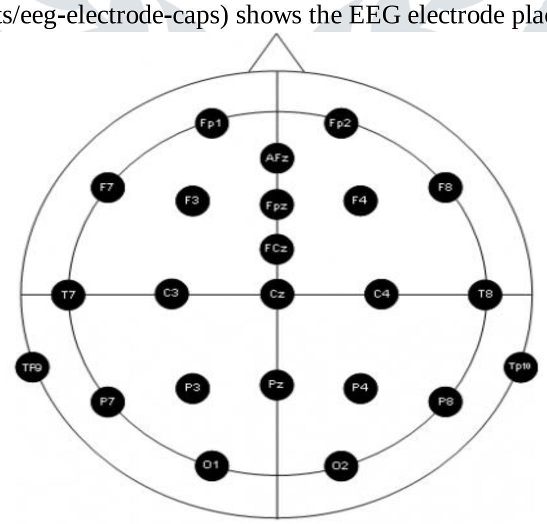


Fig 1: EEG electrode placement

Epilepsy patients uncover two phases of surprising exercises with their EEG signals i.e., ictal and interictal. Ictal is the record of an EEG while a seizure is happening (waveforms with sharp and spikes). Interictal is the period between the seizures (transient waveform i.e., spiky and sharp). By assessment of long span of EEG signals, experienced nervous system specialists with traditional technique uncovers epilepsy. Be that as it may, this technique requires long span of time and powerless against determination of blunders. Consequently Computer-helped location (CAD) of epileptic EEG sign can be used to overcome these confinements [4].

The electrical signal of brain cells usually has very small amplitude which is in the range of 100 microvolts. The frequency is in between 0.44 Hz and 80 Hz. Ordinarily, EEG signal are grouped into five sub-groups, in particular delta

(0.5-4Hz), theta (4-8Hz), alpha (8-12Hz), beta (12-30Hz) and gamma (30-60Hz). Table 1 shows the amplitude and frequency range for each type of waves [5].

TABLE I. WAVE'S FREQUENCY AND AMPLITUDE

Wave	*Frequency ranges*	*Amplitude*
Delta band	0.5 – 4 Hz	High
Theta band	4 – 8 Hz	Low-Medium
Alpha band	8 – 15 Hz	Low
Beta band	15 – 30 Hz	Very low
Gamma band	30 – 60 Hz	Smallest

In this paper, a new feature extraction technique is proposed. Variation mode decomposition (VMD) is a new adaptive signal decomposition technique which decomposes any real-time signal into band-limited functions or variation modes and extracts the features. The main purpose of feature extraction is to obtain the unique properties hidden in the EEG signals. These features are used to classify the EEG signals.

The remainder of this paper is organized as follows. In Section II literature review of existing works are presented. Section III presents detail discussion about variational mode decomposition methodology. With the methodlogy extracted features are discussed in section IV. The obtained experimental results are also discussed in this section. Finally, concluding remark of the proposed method and future work is presented in Section V.

II. RELATED WORK

In this section, the most relevant work done in EEG signal processing discussed briefly.

Pachori et al. [6] proposed Empirical mode decomposition (EMD) to extract the features from EEG signals. The EMD generates the set of amplitude and frequency modulated elements referred to as intrinsic mode functions (IMFs). Two space measures are computed, one for the graph obtained because the analytic signal illustration of IMFs within the advanced plane and another for second-order distinction plot (SODP) of IMFs of encephalogram signals. Each of those space measures are computed for initial four IMFs of the normal and epileptic seizure encephalogram signals. These eight options obtained from each space measures of 1st four IMFs are used as input feature set for classification of traditional and convulsion encephalogram signals victimization least square support vector machine (LS-SYM) classifier.

Subasi et al. [7] adopted discrete wavelet transform (DWT) to extract the features from EEG signals. The proposed method included preparing the ANFIS classifier to identify epileptic seizure in EEG when the stastical features separated from the wavelet sub-groups of EEG signal were utilized as input.

Sivasankari et al [8] demonstrate independent component analysis technique to extract the features. Improving the accuracy of EEG signal classification is exhibited to recognize epileptic seizures. ICA is consolidated as a preprocessing step and Short-Time Fourier Transform (STFT) is utilized for de-noising the sign sufficiently.

The signals were decomposed into the frequency sub-bands using DWT and a set of statistical features was extracted from the subbands to represent the distribution of wavelet coefficients. Principal components analysis (PCA), independent components analysis (ICA) and linear discriminant analysis (LDA) is used to reduce the dimension of data. Then these features were used as an input to a support vector machine (SVM) with two discrete outputs: epileptic seizure or not proposed by subasi et al. [9]

Each EEG signal is decomposed into five constituent EEG sub-bands by DWT. The nonlinear parameters of each sub-band and the original EEG are quantified in the form of the time lag (TL), the embedding dimension (ED), the correlation dimension (CD), and the largest Lyapunov exponent (LLE) adopted by hsu et al. [10]

III. PROPOSED METHOD

The aim of this work is to develop an algorithm which can detect epilepsy based on the processing of EEG signals. The suggested method uses VMD, NCFS, and machine learning algorithms. In the next section, a brief explanation and underlying mathematical expression are provided for the used techniques.

3.1 Variational Mode Decomposition

Variational mode decomposition (VMD) is a new adaptive signal decomposition technique and it decomposes any real time signal into a band limited functions or variational modes (u_k). Each mode occurred concurrently and exhibit the sparsity property for reconstruction of an input signal. VMD decomposes a real time signal into k modes (u_k) around its centre frequency (ω). Hilbert transform and frequency shifting property are useful parameters in formulation of an optimization problem. The formulation of an constrained variational problem as [11],

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \tag{1}$$

$$\sum_k u_k = f$$

The quadratic penalty factor and Lagrangian multiplier (λ) are converts into (2) from (1), The unconstrained optimization problem is expressed as (2);

$$\ell(\{u_k\},\{\omega_k\},\lambda) := \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_k u_k(t) \right\rangle$$

The alternate direction method of a multiplier (ADMM) is an optimization method to solve (2) lagrangian function ℓ, it estimate modes around its own center frequencies. The wiener filter is embedded in a VMD to update each mode $u_k(\omega)$ optimally in a spectral domain.

Steps for decomposition of EEG signals by using VMD algorithm are provided below.

Step-1: predefine K which is the number of modes.

Step-2: Initializing of $\{\hat{u}_k^1\}, \{\omega_k^1\}, \hat{\lambda}^1$, and n =0;

Step-3: For $n = n+1$, repeat loop until $k=1: K$ for $\omega \geq 0$. It keep on change $\hat{u}_k(t)$ in the spectral domain is,

$$\hat{u}_k^{n+1}(\omega) \leftarrow \frac{\hat{f}(\omega) - \sum_{i<k} \hat{u}_k^{n+1}(\omega) - \sum_{i>k} \hat{u}_k^n(\omega) + \frac{\hat{\lambda}^n(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k^n)^2} \quad (3)$$

$$\hat{u}_k^{n+1}(t) = \text{Real}\{\text{ifft}\ (\hat{u}_k^{n+1}(\omega))\} \quad (4)$$

Update ω_k with

$$\omega_k^{n+1} \leftarrow \frac{\int_0^\infty \omega\ |\hat{u}_k^{n+1}(\omega)|^2\ d\omega}{\int_0^\infty |\hat{u}_k^{n+1}(\omega)|^2\ d\omega} \quad (5)$$

Step-4: Assign $k=k+1$, repeat until k equals K and n iteration of the loop

Step-5: λ(Lagrange multiplier), updated for all ω≥0 based on dual-ascent

$$\hat{\lambda}^{n+1}(\omega) \leftarrow \hat{\lambda}^n(\omega) + \tau\left(\hat{f}(\omega) - \sum_k \hat{u}_k^{n+1}(\omega) \right) \quad (6)$$

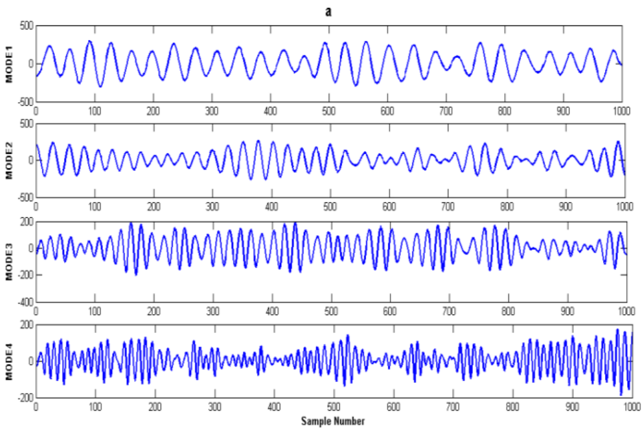
Step-6: Repeat the above steps 2 to 5 until to obtain the modes by satisfy the convergence condition.

$$\sum_{k=1}^{K} \frac{\| \hat{u}_k^{n+1} - \hat{u}_k^n \|_2^2}{\| \hat{u}_k^n \|_2^2} < \varepsilon \quad (7)$$

Here ∈ ,^ and τ represents the tolerance Fourier transform and time steps of dual ascent convergence respectively. Ifft ( ), Real ( ) are represents the inverse Fourier transform and real part of analytic signal. In VMD, the selection of a parameter is a first task, a number of modes (K), and alpha.

IV. Results and Discussion

The mode decomposition of normal and epilepsy EEG signals are in Figure 2a, Figure 2b shown respectively. It signifies that the mode increases also its frequency increases.



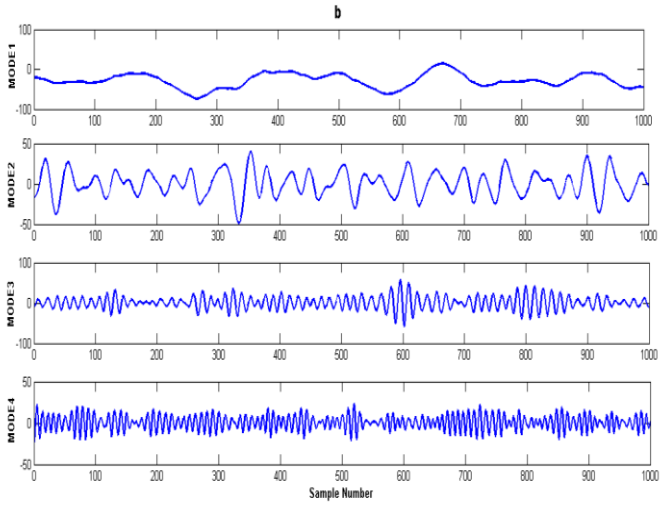


Fig. 1. VMD of four modes (a) Epilepsy signal (b) Normal EEG signal examples

4.1 Feature extraction:

1) Statistical features:

For an N sample EEG signal *y[n]* gives the magnitude spectrum of *Y[m]*.

Statistical features:

Mean: It is the average of an N sample EEG signal; it can be defined [12],

$$\mu = \frac{1}{N}\sum_{i=1}^{N} Y_i \qquad (8)$$

Standard deviation: The dispersion of data from it's a mean value of a signal is a standard deviation. It is derived as [16],

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(Y_i-\mu)^2} \qquad (9)$$

Coefficient of variation (COV): The ratio of standard deviation to mean value of the EEG signal is a coefficient of variation. It can be expressed as [12].

$$COV = \frac{\sigma}{\mu} \qquad (10)$$

Entropy (H): It is defined as the measuring of randomness in EEG signals. For an EEG signals with N number of samples (y_1, y_2, y_3,…. Y_N) is expressed as [12],

$$H(Y) = -\sum_{i=1}^{N} p(y_i)\log(p(y_i)) \quad p(y_i) = [p(y_1), p(y_2)......] \qquad (11)$$

Inter quartile range (IQR): It is defined as the difference between 75th and 25th percentile of samples, It measures variability in a data set is given by [13],

$$IQR = Q_3 - Q_1 \qquad (12)$$

Here, Q3 and Q1 are third and first quartile respectively.

Skewness: It measures the symmetry shape of the distribution of a signal, It can be derived as

$$\text{Skewness} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i-\mu}{\sigma}\right)^3 \qquad (13)$$

NegEntropy: The differences between gaussian entropy H(Ygauss) and differential entropy H(Y) having mean μ and variance σ^2 of EEG signals. It is expressed as [12],

$$J(Y) = H(Y_{gauss}) - H(Y) \qquad H(Y_{gauss}) = \frac{1}{2}\log(2\pi e\sigma^2) \qquad (14)$$

Kurtosis: It is a one of the statistical moment; it gives the time series data peaked nature. Kurtosis can be derived as [13]

$$k = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i-\mu}{\sigma}\right)^4 \qquad (15)$$

2) Spectral features :

Spectral flatness (SF): Spectral flatness can be define as the ratio of magnitude spectrum of geometric mean to the arithmetic mean, It can be expressed as [12,14],

$$SF = \frac{\prod_{m=0}^{N-1}|Y[m]|^{\frac{1}{N}}}{\frac{1}{N}\sum_{m=0}^{N-1}|Y[m]|} \qquad (16)$$

Spectral spread (SS): Average deviation of a magnitude spectrum around its spectral centroid is called as spectral spread. It can also be assumed as instantaneous bandwidth, It can be mathematically expressed as [12,14],

$$SS = \frac{\sum_{m=0}^{N-1} (m - SC)^2 |Y[m]|}{\sum_{m=0}^{N-1} |Y[m]|} \tag{17}$$

It is a ratio of sum of a weighted magnitude spectrum to normalized by an unweighted sum is called as spectral centroid (SC),

$$SC = \frac{\sum_{m=0}^{N-1} m|Y[m]|}{\sum_{m=0}^{N-1} |Y[m]|} \tag{18}$$

Spectral decrease (SDec): It measuring the amount of decrease of a spectral envelope of a signal with respect to frequency, it is denoted as [12],

$$SDec = \frac{\sum_{m=1}^{N-1} \frac{1}{m}.\left(|Y[m]| - |Y[0]|\right)}{\sum_{m=1}^{N-1} |Y[m]|} \tag{19}$$

The EEG dataset is received from the Bonn University Hospital of Freiburg [15]. It contains five individual subsets (set A to E) named as Z, O, N, F and S. Every subset comprises 23.6s length of 100 single channel EEG signals. The information has an inspecting pace of 173.61 Hz and digitalized with 12-bit simple to advanced goals. Set A and set B are caught extra cranially though staying gathered intracranial with an institutionalized 10-20 electrode system. Set A was recorded from the healthy patients when eyes open, set B was recorded from the healthy patients when eyes close, Set C and set D were recorded when patients are in seizure free interims, Set E comprises of epileptic seizure signals and these signal show ictal movement.

In this paper, the proposed approach initially chopped signal into four parts after that performs variable mode decomposition on various epilepsy and normal signals to extract the statistical and spectral features. An effective feature extraction method for EEG is developed by decomposing the signal into four level for both training and testing sets and totally 44(11x4) features are calculated and listed in Table-II, Table-III and Table-IV.

TABLE II. EXTRACTED FEATURE VALUES OF THE COV, ENTROPY, IQR, MEAN

Mode no.	Signal type	COV	Entropy	IQR	Mean
Mode 1	Normal	3.060578	0.987282	22.41976	8.047045
	Epilepsy	5.716333	1.005897	279.9625	33.16918
Mode 2	Normal	81.99665	1.349727	20.81052	0.199004
	Epilepsy	50.06591	1.009621	278.19	4.233459
Mode 3	Normal	478.6373	1.268943	20.96115	0.037816
	Epilepsy	222.5204	1.020629	263.7505	0.827009
Mode 4	Normal	681.7987	1.580045	10.02937	0.011917
	Epilepsy	316.3635	1.041619	199.9717	0.469569

TABLE III. EXTRACTED FEATURE VALUES OF THE NEG ENTROPY, KURTOSIS, SDEC, SF

Mode no.	Signal type	Neg entropy	Kurtosis	Spectral decrease	Spectral flatness
Mode 1	Normal	3.635565	475.7437	-0.25047	0.181466
	Epilepsy	5.657991	491.4882	-0.09061	0.346001
Mode 2	Normal	2.861461	500.2766	0.009986	0.187271
	Epilepsy	5.765677	499.8695	-0.00068	0.273621
Mode 3	Normal	3.045915	500.8829	0.007408	0.210042
	Epilepsy	5.613389	500.7571	0.003921	0.271984
Mode 4	Normal	1.933808	500.9316	0.004644	0.197187
	Epilepsy	5.37827	500.8314	0.003417	0.17237

Table IV. EXTRACTED FEATURE VALUES OF THE SKEWNESS, SPECTRALSPREAD, STANDARD DEVIATION

Mode no.	Signal type	Skewness	Spectral Spread	Standard Deviation
Mode 1	Normal	-0.9222	221593.3	24.62861
	Epilepsy	0.32328	198496.5	189.6061
Mode 2	Normal	-0.21098	207717.5	16.31769
	Epilepsy	-0.13853	192989.2	211.952
Mode 3	Normal	-0.01665	181230.8	18.10015
	Epilepsy	-0.03184	164691.8	184.0264
Mode 4	Normal	0.009716	149595.5	8.124754
	Epilepsy	-0.0319	152207.6	148.5544

V. CONCLUSION

Electroencephalogram (EEG) is an important means of identifying and analyzing epileptic seizure activity in humans. The discovery of epileptic seizure being performed by visual examining of EEG signal is very tedious, expensive system and might be wrong, explicitly for quite a while EEG recording. In this paper, the proposed methodology at first slashed signal into four sections after that performs variable mode decomposition on different epilepsy and normal signals to extract the statistical and spectral features. A successful feature extraction strategy for EEG is created by decomposing the signal into four level. From each level eleven features are extracted totally 44 features are extracted from each signal. In the future work these features are effectively used to classify the different EEG signals (epilepsy and Normal) with the help of machine learning algorithms like artificial neural network, K-nearest neighbor, Support vector machine etc.

REFERENCES

[1] Z. Lasefr, Sai Shiva V N R Ayyalasomayajula, and K. Elleithy, “An efficient automated technique for epilepsy seizure detection using EEG signals,” In Proc. IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON), pp. 76-82, 2017.

[2] Acharya, U. Rajendra, et al. "Application of entropies for automated diagnosis of epilepsy using EEG signals: a review." Knowledge-Based Systems 88 (2015): 85-96.

[3] Kalaivani, M., V. Kalaivani, and V. Anusuya Devi. "Analysis of EEG Signal for the Detection of Brain Abnorrnalities." JJCA Proceedings on International Conference on Simulations in Computing Nexus. No. 2. Foundation of Computer Science (FCS), 2014.

[4] SK. Ebraheem Khaleelulla and Dr. P. Rajesh Kumar, “a novel statistical approach for detection and classification of epileptic seizures using DWT and SVM, ” International Journal of Current Engineering and Scientific Research (IJCESR), Vol. 5, No. 3, pp. 1-7, 2018.

[5] Ebraheem Khaleelulla S., Rajesh Kumar P. (2018) EEG Signal Analysis for Mental States and Conditions of Human Brain. In: Satapathy S., Bhateja V., Chowdary P., Chakravarthy V., Anguera J. (eds) Proceedings of 2nd International Conference on Micro-Electronics, Electromagnetics and Telecommunications. Lecture Notes in Electrical Engineering, vol 434. Springer, Singapore

[6] Pachori, Ram Bilas, Rajeev Sharrna, and Shivnarayan Patidar. "Classification of normal and epileptic seizure EEG signals based on empirical mode decomposition." Complex System Modelling and Control Through Intelligent Soft Computations. Springer International Publishing, 2015. 367-388.

[7] Subasi, Abdulhamit. "Application of adaptive neuro-fuzzy inference system for epileptic seizure detection using wavelet feature extraction." Computers in Biology and Medicine 37.2 (2007): 227-244.Abdurrahaman, Ismail M and Ramzan “Regularization And Kernel Parameters Optimization Based On PSO Algorithm In EEG Signals Classification With SVM”, 2011 IEEE 19th Signal Processing and Communications Applications Conference (SIU 2011):399-402.

[8] Sivasankari, K., and K. Thanushkodi. "An improved EEG signal classification using neural network with the consequence of ICA and STFT." Journal of Electrical Engineering and Technology 9.3 (2014): 1060-1071.

[9] Subasi, Abdulhamit, and M. Ismail Gursoy. "EEG signal classification using PCA, ICA, LDA and support vector machines." Expert Systems with Applications 37.12 (2010): 8659-8666.

[10] Hsu, Kai-Cheng, and Sung-Nien Yu. "Detection of seizures in EEG using subband nonlinear parameters and genetic algorithm." Computers in Biology and Medicine 40.10 (2010): 823-830.

[11] LerchA.”An introduction to audio content analysis: applications in signal processing and music informatics”. Hoboken: Wiley; 2008

[12] Taran S, Bajaj V, Sharma D. Robust “Hermite decomposition algorithm for classifcation of sleep apnea EEG signals”. Electron Lett. 2017;53(17):1182–4.

[13] Hassan AR, Haque MA. “Computer-aided obstructive sleep apnea screening from single-lead electrocardiogram using statistical and spectral features and bootstrap aggregating”. Biocybern Biomed Eng. 2016;36(1):256–66.

[14] R. Panda, P. Khobragade, P. Jambhule, S. Jengthe, P. Pal, and T. Gandhi, "Classification of EEG signal using wavelet transform and support vector machine for epileptic seizure diction," in Systems in Medicine and Biology (ICSMB), 2010 International Conference on, 2010, pp. 405-408.
(eds.), Morgan Kaufmann, pp.249-256.

[15] R. G. Andrzejak et al., “Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: dependence on recording region and brain state,” Phys. Rev. E, vol. 64, no. 6, pp. 116-126, Nov. 2001.