Classification of Epileptic Resting-State Electroencephalogram Signals Based on Machine Learning and Cross-Spectrum Features

1st José Fiel
Electrical Engineering Graduate Program
Federal University of Pará
Belém, Brazil
jose.fiel@itec.ufpa.br

2nd Thaynara Ribeiro
Dept. of Biomedical and Electrical Engineering
Federal University of Pará
Belém, Brazil
thaynara.ribeiro@itec.ufpa.br

3rd Eline Melo
Neuroscience and Cell Biology Graduate Program
Federal University of Pará
Belém, Brazil
eline.melo@icb.ufpa.br

4th Raphael Navegantes
Electrical Engineering Graduate Program
Federal University of Pará
Belém, Brazil
raphael.navegantes@itec.ufpa.br

5th Francinaldo Gomes
Ophir Loyola Hospital
Belém, Brazil
francinaldogomes2012@hotmail.com

6th Antonio Pereira
Electrical Engineering Graduate Program
Neuroscience and Cell Biology Graduate Program
Federal University of Pará
Belém, Brazil
apereira@ufpa.br

***Abstract*—We used machine learning tools to discriminate resting-state brain electrical activity measured with electroencephalography (EEG) of patients with refractory epilepsy (RE) from healthy controls (HC). We propose a cross-spectral density-based measure as a signal feature to distinguish between healthy and epileptic subjects using machine-learning algorithms linear discriminant analysis (LDA) and support vector machines (SVM). The resting-state EEG of epileptic patients were obtained from interictal periods without any epileptiform activity. We recorded from 11 epilepsy patients and 7 healthy age-matched controls. Both algorithms obtained 100 % accuracy. Our results show that a distinction between the two groups is possible with high accuracy when a 190-dimensional feature vector is used as input.**

Keywords—cross-spectrum density, debiased weighted phase-lag index, electroencephalography, epilepsy, machine learning

I. Introduction

Epilepsy is characterized as the transient occurrence of signs and symptoms due to excessive, hypersynchronous neuronal activity in the brain. Epilepsy affects over 70 million people worldwide [1], [2] with approximately 80 % of them living in low-income and middle-income countries [2]. The patients' quality of life, their households and the public healthcare systems have the potential to be negatively affected by the disease [3]. Moreover, a large number of patients (about 75 %) remain untreated [4].

Recording brain's electrical activity with electroencephalography (EEG) continues to be one of the most important approaches to support a diagnosis of epilepsy, which is complex and also based on many symptoms and signs. The diagnosis is based on the presence of electrophysiological features such as interictal spikes, sharp waves, and other abnormal patterns [5]. The interpretation of EEG is a pattern-recognition skill usually based on visual analysis by trained experts. However, misinterpretation of EEG is common and can have negative impacts of patients' outcomes. Thus, the introduction of automatic computerized tools might improve the quality of epilepsy diagnosis and benefit many patients, especially in low-income countries.

Machine learning and pattern recognition algorithms are frequently used to find intrinsic patterns in complex data [6]. These algorithms allow the automatic discrimination of two or more categories without relying on a predetermined equation as a model. After a training phase, a machine learning algorithm can generalize its performance and assign new events to predefined classes. Machine learning is increasingly being used in different biomedical applications to access relevant information available in complex EEG signals, including neural engineering [7] and medical diagnosis [8]. The key steps involved in implementing a high-performance machine learning classification algorithm includes shaping the problem into a suitable framework and identifying appropriate features to categorize brain activity associated with the different groups of interest [9]. Nonetheless, this is a challenging problem in neuroscience because the dynamics of brain's electrical activity is nonlinear and composed of numerous classes with non-stationary overlapping characteristics [10], [11]. Thus, the input formulations used for training the machine learning algorithms have to be carefully chosen [12].

Network analysis has been used to describe patterns of organization in complex systems comprising multiple dynamically interacting agents, such as the human brain [13]. Graph theory has been successfully applied to characterize how interacting neuronal groups distributed in the brain underlie human behavior [14], [15]. For instance, neurologic diseases have been linked to suboptimal organization of the brain default-mode network (DMN) [16]–[21]. One of the aims of network neuroscience is to explain the differences in brain network organization between healthy individuals and patients with distinct neurological disorders [22], [23]. Hence, in the present work, we propose a network-based cross-spectral density-based measure, debiased weighted phase-lag index (dWPLI), as an input feature for machine learning algorithms. The dWPLI is based on the consistency of the phase differences between two signals [24].

The main contribution of this paper is to demonstrate the feasibility of combining machine learning algorithms and a cross-spectral density feature to identify brain activity of RE patients using short periods of interictal resting-state EEG signals. To the best of our knowledge, no other similar approach has been applied to resting state EEG recordings. Previously, other two studies used machine-learning techniques do discriminate brain activity of healthy and epileptic subjects, one used magnetoencephalogram (MEG), a procedure which is much costlier than EEG [25], and the other used resting-state EEG recordings from children with partial epilepsy [26]. The sensitivity and specificity of the latter model was nonetheless high (0.96 and 0.95, respectively). The content of this study is organized as follows: in Subsection II.A the EEG recording and preprocessing are described; the feature selection is presented in Subsection II.B; theoretical information about the methods used for machine-learning classification are provided in Subsection II.C; in Subsection II.D, we define the metrics used to evaluate the performance of the classifiers; the experimental results are presented in Section III and discussed in Section IV. We discuss the relevance of our proposed method in Section V.

II. Material and Methods

The protocol proposed to classify the brain activity of epilepsy patients and healthy subjects is displayed in Fig. 1. The major steps of the protocol are described as follows.

A. *Data Acquisition and Preprocessing*

Resting-state EEG were recorded from 11 patients diagnosed with epilepsy and 7 healthy control subjects. EEG was recorded with a 22-channel system (Neuromap40i, Neurotec, Itajubá, Brazil) with a sampling frequency of 256 Hz and using Fpz as ground. Channels were referenced to the linked mastoids. The electrodes' impedance was kept below 20 kΩ. This work was approved by our institution's Ethics Committee (2.432.373).

The recordings were preprocessed with the Matlab R2017a (The Mathworks, Inc., Natick, MA, United States) toolbox EEGLAB [27]. Artifacts such as swallowing, head movement, and electromyogram were manually removed. Time windows containing amplitudes bigger than 50 µV were also manually removed. Then, we select nine minutes of the remaining recording to further preprocess the EEG. Data were then high passed at 0.5 Hz to remove slow drift and DC offsets. We used independent component analysis (ICA) to remove blink and muscle artifacts, as well as other non-biological artifacts.

B. *Feature Extraction and Selection*

We extracted a cross-spectrum based feature from the EEG recordings based on phase differences between pairs of EEG electrodes, named debiased weighted phase-lag index (dWPLI) [24]. Similar to other phase-lag measures the dWPLI is robust against volume conduction artifacts. The other advantages of the dWPLI are: 1) its negligibly small sampling bias and 2) its improved capacity to detect true differences in phase synchronization due to its lower sensitivity to noise as compared to the previously suggested phase-lag index (PLI) [24]. We estimated the dWPLI between the EEG channels x and y using (1) [24].

$$dWPLI = \frac{\sum_{j=1}^{N}\sum_{j\neq k}^{N}\Im\{S_{xy}^{j}\}\Im\{S_{xy}^{k}\}}{\sum_{j=1}^{N}\sum_{j\neq k}^{N}\left|\Im\{S_{xy}^{j}\}\Im\{S_{xy}^{k}\}\right|} \quad (1)$$

Where $\Im\{S_{xy}^{j}\}$ is the imaginary component of the cross-spectrum between x and y at the time windows j; N is the total number of time windows analyzed; and the value dWPLI ∈ [0,1]. The cross-spectrum is computed multiplying the Fourier spectrum of the channel x by the complex conjugate of the Fourier spectrum of channel y. We estimated dWPLI in Matlab using the FieldTrip toolbox [28]. We defined three frequency bands of interest: θ (4-8 Hz), α (8-13 Hz), and β (13-30 Hz) for dWPLI estimation.

C. *Machine Learning Algorithms*

We applied two classifier models to the data. The input to the classifiers is a vector with real-valued elements computed as in (1).

1) Linear Discriminant Analysis (LDA): LDA is a classification method used to separate two or more classes based on a chosen feature [6]. LDA can be implemented in four steps: 1) assume a feature vector x whose elements have to be assigned to either two possible classes G = {k,l}; 2) let $f_k(x)$ be the class-conditional density of x in class G = k, and let π_k be the prior probability of class k; 3) model the two classes with multivariate Gaussian densities and assume they have a common covariance matrix Σk = Σl = Σ; 4) compare the log-ratio (L(x)) of the posterior probabilities of the two classes and find the boundary coefficients (β values) that allows us to discriminate the classes using (2) [6], as long as the constraints in (3) hold.

$$\begin{cases} L(x) = \log\left(\dfrac{\Pr(G=k|X=x)}{\Pr(G=l|X=x)}\right) \\ L(x) = \log\left(\dfrac{f_k(x)\pi_k}{f_l(x)\pi_l}\right) = \beta_0 + x^T\beta \end{cases} \quad (2)$$

$$\begin{cases} \beta_0 = \log\dfrac{\pi_k}{\pi_l} - \dfrac{1}{2}(\mu_k-\mu_l)^T\Sigma^{-1}(\mu_k+\mu_l) \\ \beta = (\mu_k-\mu_l)^T\Sigma^{-1} \end{cases} \quad (3)$$

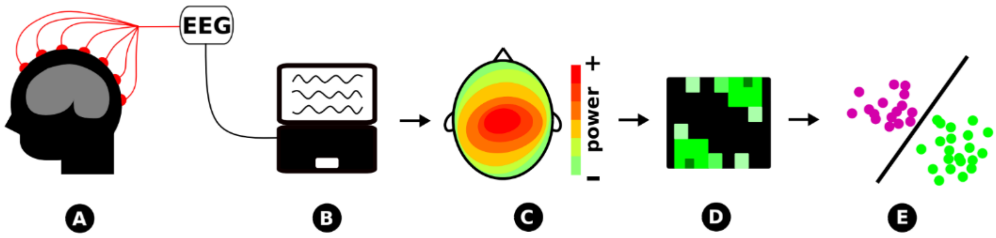

Fig. 1. Experimental design. First, (A) the EEG data is recorded from participants. Then, (B) the signals are preprocessed to remove artifacts. (C) Power spectra are computed, and (D) the pairwise connectivity of the channels is estimated. Finally, (E) linear classifiers differentiate the feature vectors.

Therefore, in order to estimate the coefficients (β_0 and β) that define the boundary of the classes, we only need to know the mean value (μ_k and μ_l) for each class, the variance (Σ) calculated across all classes, and the prior probability (π_k and π_l) of each class. We assign x to G = k if the logarithm of the two posterior probabilities is greater than zero (i.e., L(x) > 0). Otherwise, we assign x to G = l.

2) Support Vector Machine (SVM): SVM algorithms are included in the category of hyperplane classifiers, which attempt to separate datasets into different classes by creating linear decision boundaries. These boundaries are named hyperplanes and the distance between the hyperplane and the closest data points is referred to as the margin [8]. It is possible to find an optimally separating hyperplane by minimizing the distance of misclassified points to the decision boundary [8]. Assuming $y_i = \{-1, +1\}$, if a response y_i =+1 is misclassified, then $x^T \beta + \beta_0 < 0$, and the opposite happens to a misclassified response with $y_i = -1$. The goal is then to minimize in (4).

$$D(\beta, \beta_0) = -\sum_{i \in \mathcal{M}} y_i (x^T \beta + \beta_0) \tag{4}$$

Where M indexes the set of misclassified points [6]. A hyperplane is defined by the coefficients β and β_0 as $x^T \beta + \beta_0 = 0$. Supposing the training data consists of N pairs (x1; y1), (x2; y2), …, (xN; yN), with xi ∈ IR, we can find a hyperplane that creates the biggest margin between the training points for the two classes using a optimization problem given by (5), subject to: $x^T \beta + \beta_0 > 1 - \xi_i$, $\xi_i \geq 0$; and $\sum \xi_i \leq$ constant.

$$\min_{(\beta,\beta_0)} \|\beta\|, \forall i \tag{5}$$

D. *Algorithm's Performance*

To evaluate the algorithm's performance, we chose three measures: average accuracy, sensitivity, and specificity. We were able to compute those measures based on the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). A k-fold cross validation (with k = 5) was applied in order to calculate the average accuracy. In the 5-fold cross validation, the dataset is split into 5 groups. Then, one group is used for testing while the other 4 are used for training. Accuracy was calculated according to (6). This process was applied to each classifier, thus we used 80 % of the data set for training, and 20 % for testing. The sensitivity and the specificity were calculated using (7) and (8), respectively. The results obtained by the simulations are quantified as follows.

$$accuracy = \frac{TN+TP}{TP+TN+FN+FP} \tag{6}$$

$$sensitivity = \frac{TP}{TP+FN} \tag{7}$$

$$specificity = \frac{TN}{TN+FP} \tag{8}$$

We also used the area under a receiver operating characteristic (AUROC) as a measurement of performance discrimination. The AUROC measures the ability of the classifier to correctly identify those subjects with and without the epileptic condition [25]. Values above 0.50 indicate discriminatory ability. When the AUROC approaches 1, the algorithm is said to have excellent discriminatory power, while an area of 0.50 represents the same classification as in a random guess.

III. Results

A total of 13021 samples were extracted (7585 for RE class, 5436 for HC class). Table I provides details about the input data. Training and test data sets were randomly chosen in the cross-validation process. Each vector sample contained 190 features. We further varied the number of features by selecting different regions of interest to analyze the effects of dimensionality reduction on the classification. The regions of interest (ROIs) are displayed in Fig. 2 and include all the electrodes located within a given ROI. We tested our system using an Intel Core i7-4510U Processor (2.6 GHz) with 8 GB DDR3-SDRAM (2 × 4) GB.

TABLE I. Amount of Data Used for Training and Testing of the Classifiers

Step	Proportion of total set size (%)	Number of sets
Training	80	10417
Testing	20	2604
Total	100	13021

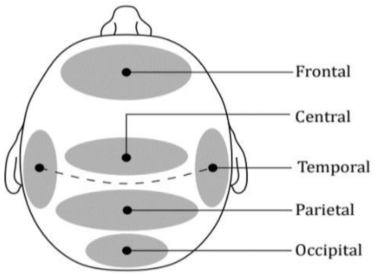

Fig. 2. Regions of Interest: frontal (F), parietal (P), temporal (T), and occipital (O).

Grand average dWPLI plots for each group are displayed in Fig. 3, as square connectivity matrices of dimensions 20 x 20 (channel x channel). The frequency bands of interest were defined as θ, α, and β. We can see that synchronization is higher between channels in the RE group for the three frequency bands of interest. Our method was able to differentiate the groups using interictal EEG signals. The differences for the three bands displayed in Fig. 3 further corroborate what is found in the literature, as epilepsy has been historically linked to the hypersynchronization of neuronal populations [29].

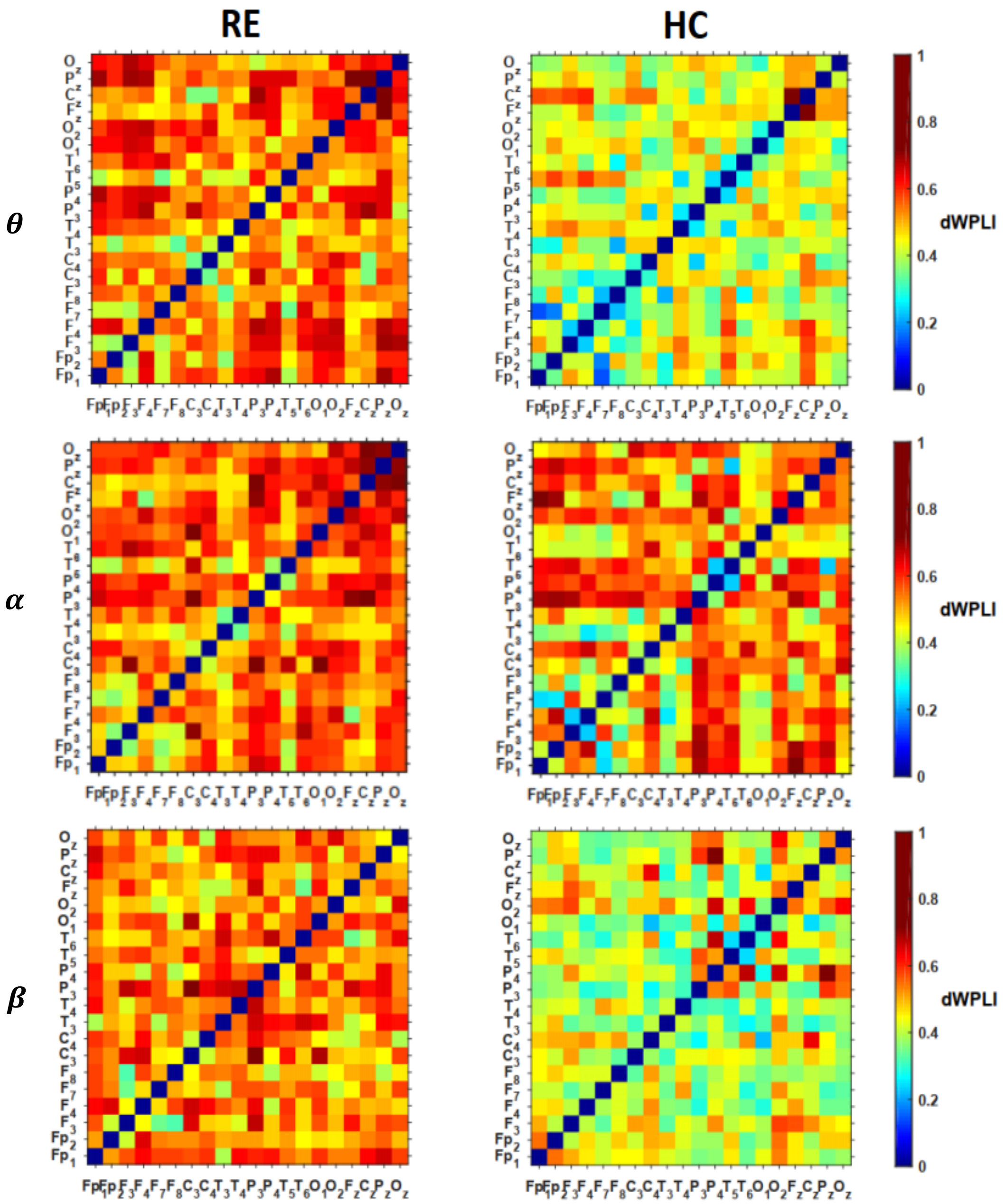

Fig. 3. Grand average dWPLI across subjects per sensor for RE and HC groups in the bands of interest: θ, α, and β. dWPLI is defined along the interval 0-1, where 1 represents perfect phase syncronization.

TABLE II. AVERAGE RESULTS OBTAINED BY THE CLASSIFIERS ACCORDING TO THE NUMBER OF FEATURES USED AS INPUT FOR 5-FOLD CROSS-VALIDATION

Band	Connections	Number of features	Accuracy (%)		Sensitivity (%)		Specificity (%)		AUROC	
			SVM	LDA	SVM	LDA	SVM	LDA	SVM	LDA
θ	F-T	14	79.92	78.16	75.66	75.24	83.82	80.40	0.89	0.88
	F-T, P-T	24	88.01	87.78	88.53	90.49	86.93	86.13	0.94	0.95
	F-O, P-O	36	87.62	89.13	90.07	86.85	84.92	89.85	0.94	0.95
	F-T, F-P	49	97.23	97.32	97.20	96.50	97.39	97.89	0.99	**1**
	F-O, P-O. F-T, P-T	60	96.16	97.72	97.90	98.46	94.77	97.59	0.99	**1**
	all combinations	190	**100**	**100**	**100**	**100**	**100**	**100**	**1**	**1**
α	F-T	14	87.98	85.07	90.40	87.15	85.50	83.93	0.92	0.91
	F-T, P-T	24	95.53	93.99	96.60	95.90	95.20	93.00	0.99	0.99
	F-O, P-O	36	97.86	97.40	97.80	98.10	97.80	96.70	**1**	**1**
	F-T, F-P	49	99.99	99.83	99.90	100	100	99.80	**1**	**1**
	F-O, P-O. F-T, P-T	60	99.67	99.80	99.50	100	99.70	99.30	**1**	**1**
	all combinations	190	**100**	**100**	**100**	**100**	**100**	**100**	**1**	**1**
β	F-T	74	76.29	75.61	93.77	89.23	51.39	56.19	0.79	0.79
	F-T, P-T	24	85.66	84.18	91.35	92.57	77.77	72.40	0.93	0.93
	F-O, P-O	36	89.46	88.40	95.05	94.82	81.57	79.41	0.94	0.94
	F-T, F-P	49	91.69	90.47	95.18	94.75	86.69	84.43	0.97	0.96
	F-O, P-O. F-T, P-T	60	97.50	96.03	98.88	98.68	95.61	92.12	**1**	0.99
	all combinations	190	**100**	**100**	**100**	**100**	**100**	**100**	**1**	**1**

Using only 14 features (frontal and temporal connections) extracted from the connectivity matrix as the input feature vector, the algorithms performed best in the α band. In these case, SVM and LDA algorithms achieved average accuracy of 87.98 % and 85.07 %, respectively. Correspondingly, we found the higher values for sensitivity and specificity in the α band. SVM method presented average sensitivity of 90.40 %, and average specificity of 85.50 %, meanwhile LDA algorithm achieved average sensitivity and average specificity of 87.15 % and 83.93 %, respectively.

From Table II we can see that the average accuracy gradually increases while increasing the number of input dimensions. Not surprisingly, the maximum accuracy for each classifier was achieved using a 190-dimensional feature vector as input. In this case, SVM and LDA algorithms performed similarly, with 100 % of average accuracy, sensitivity, and specificity (see Table II). Similarly, we found that AUROCs were higher when input vectors with 190 features were used. In summary, both SVM and LDA algorithms performed better in the α band (see Table II).

In order to analyze whether the proposed methods can reduce the time-consuming identification of epilepsy patients, we computed the average execution time of each step (see Fig. 1) over 100 simulations. We used classifiers trained with 190 features as input and we performed 100 simulations for each classifier (see Table III). We found the ICA is the bottleneck step in our EEG preprocessing pipeline, given its time-consuming computation. The average execution time of ICA accounts for more than 75 % of the entire pipeline execution time. Considering all steps involved, the average time required for correct identification of the EEG was up to 403.82 s (for SVM method).

TABLE III. EXECUTION TIMES FOR THE PROCESSING PIPELINE

Step		Execution time (s)
Load data		23.33
Compute ICA		304.72
Band pass filter		2.33
Power spectra estimate		56.71
Extract and select features		16.95
Online classification	**LDA**	0.07
	SVM	0.08
Toal time	**LDA**	403.81
	SVM	403.82

IV. DISCUSSION

Classification of EEG signals using both ternary and binary algorithms have been proposed. Ternary methods attempt to differentiate non-epileptic from epileptic EEG signals. To do so, the signals are defined as belonging to one of the three following groups: non-epileptic (normal), interictal, and ictal. Meanwhile, binary classifiers attempt to differentiate two groups usually as: 1) normal or interictal, 2) normal or ictal, and 3) interictal or ictal. A great number of methods for classification of EEG signals achieved 100 % accuracy for cases 2) and 3) [30]–[35]. The maximum accuracy achieved in these works may be due to the fact that ictal EEG represents an extreme scenario of hypersynchronization of neuronal populations, which radically differs from normal and interictal EEG.

A classification technique using variational mode decomposition with an auto-regression based quadratic feature extraction and a random forest classifier is proposed in [36] achieved accuracy of 97.40 % for ternary (normal vs interictal vs ictal) EEG classification. [30] proposed a data dependent method, which consists in a modified wavelet transform combined with a multi-scale entropy measure as feature for an SVM classifier. The method achieved accuracy of 98.6 % for ternary classification (normal vs seizure-free vs seizure). However, besides being data-dependent, this technique requires the manual tuning of the parameters, which is another disadvantage of this approach [30]. The method proposed in [32] uses a discrete wavelet transform for feature extraction and naïve Bayes and k-nearest neighbors as binary (epileptic vs non-epileptic) classifiers. The method's accuracy ranged from 96.40 % to 99.60 % when the data set include normal, interictal and ictal EEG signals. A possible pitfall for this method is the lack of cross-validation that can lead to inflated results [37]. A robust method for both binary (epileptic vs non-epileptic and ictal vs interictal) and ternary (normal vs interictal vs ictal) EEG classification is proposed in [35]. This method is based on deep learning (DL) algorithms. DL algorithms are not data dependent and can automatically adapt to the internal structure of the data set, which enhances their generalization power. They proposed a pyramidal 1D convolutional neural network (P-1D-CNN) model for detecting epilepsy and reported accuracies ranging from 99.10 % to 99.97 % for different data sets. DL approaches, however, require large amount of data for training. Thus, [35] proposed two augmentation schemes. Another disadvantage of the P-1D-CNN method is that it requires computers with graphic processing units (GPU).

The performance measure of our method has been found to be comparable with other existing state-of-the-art classification approaches found in the literature. Even though we have not used ictal EEG signals, we have achieved 100 % accuracy for binary classification using simple linear classifiers. [25] also combined machine learning algorithms with functional connectivity analysis with interictal MEG recordings, however, they achieved accuracy of 90 % for binary (epileptic vs non-epileptic) classification. [26] used EEG to build a prediction model for diagnosis of partial epilepsy in children with good performance. Our study extends the findings from these previous works, showing that a specific measure of EEG connectivity for theta, alpha, and beta frequency bands, dWPLI, can be used to improve accuracy in diagnosing epilepsy in adults.

V. Conlusions

In this study, we applied machine learning techniques to discriminate epileptic patients from healthy controls based on a cross-spectrum feature extracted from their resting-state EEG signals. The input feature for the machine learning classifiers was derived from a network-based approach relying on spectral phase distributions obtained from pairwise comparisons of EEG channels, called dWPLI. As a comparative measure, we analyzed the impact of varying the number of features used as input on the performance of the classifiers. The framework proposed yielded average accuracy classification of 100 % using 190-dimensional input vector for both SVM and LDA algorithms. In summary, we successfully applied a dWPLI measure as an input to machine learning algorithms in order to discriminate between EEG signals of healthy and epileptic subjects. This result may contribute to further establish the power of machine learning algorithms as tools to build automated systems able to reliably diagnose epilepsy.

References

[1] L. Kuhlmann, K. Lehnertz, M. P. Richardson, B. Schelter, and H. P. Zaveri, "Seizure prediction — ready for a new era," *Nature Reviews Neurology*, vol. 14, no. 10, pp. 618–630, Oct. 2018.

[2] R. D. Thijs, R. Surges, T. J. O'Brien, and J. W. Sander, "Epilepsy in adults," *Lancet*, vol. 393, no. 10172, pp. 689–701, 16 2019.

[3] I. Megiddo, A. Colson, D. Chisholm, T. Dua, A. Nandi, and R. Laxminarayan, "Health and economic benefits of public financing of epilepsy treatment in India: An agent-based simulation model," *Epilepsia*, vol. 57, no. 3, pp. 464–474, 2016.

[4] S. Saxena and S. Li, "Defeating epilepsy: A global public health commitment," *Epilepsia Open*, vol. 2, no. 2, pp. 153–155, 2017.

[5] R. S. Fisher *et al.*, "ILAE Official Report: A practical clinical definition of epilepsy," *Epilepsia*, vol. 55, no. 4, pp. 475–482, Apr. 2014.

[6] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition*, 2nd edition. New York, NY: Springer, 2016.

[7] F. Lotte *et al.*, "A review of classification algorithms for EEG-based brain-computer interfaces: a 10 year update," *J Neural Eng*, vol. 15, no. 3, p. 031005, 2018.

[8] E. Alpaydin, *Introduction to Machine Learning*, 3rd edition. MIT Press, 2009.

[9] S. Khalid, T. Khalil, and S. Nasreen, "A survey of feature selection and feature extraction techniques in machine learning," *2014 Science and Information Conference*, pp. 372–378, 2014.

[10] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "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 Stat Nonlin Soft Matter Phys*, vol. 64, no. 6 Pt 1, p. 061907, Dec. 2001.

[11] C. J. Stam, "Nonlinear dynamical analysis of EEG and MEG: review of an emerging field," *Clin Neurophysiol*, vol. 116, no. 10, pp. 2266–2301, Oct. 2005.

[12] A. Craik, Y. He, and J. L. Contreras-Vidal, "Deep learning for electroencephalogram (EEG) classification tasks: a review," *J. Neural Eng.*, vol. 16, no. 3, p. 031001, Apr. 2019.

[13] M. A. Kramer and S. S. Cash, "Epilepsy as a disorder of cortical network organization," *Neuroscientist*, vol. 18, no. 4, pp. 360–372, Aug. 2012.

[14] E. Bullmore and O. Sporns, "Complex brain networks: graph theoretical analysis of structural and functional

systems," *Nat. Rev. Neurosci.*, vol. 10, no. 3, pp. 186–198, Mar. 2009.

[15] W. Liao *et al.*, "Altered Functional Connectivity and Small-World in Mesial Temporal Lobe Epilepsy," *PLoS ONE*, vol. 5, no. 1, p. e8525, Jan. 2010.

[16] K. M. Albert, G. G. Potter, B. D. Boyd, H. Kang, and W. D. Taylor, "Brain network functional connectivity and cognitive performance in major depressive disorder," *Journal of Psychiatric Research*, vol. 110, pp. 51–56, Mar. 2019.

[17] R. L. Buckner, J. R. Andrews-Hanna, and D. L. Schacter, "The Brain's Default Network," *Annals of the New York Academy of Sciences*, vol. 1124, no. 1, pp. 1–38, 2008.

[18] F. X. Castellanos *et al.*, "Cingulate-Precuneus Interactions: A New Locus of Dysfunction in Adult Attention-Deficit/Hyperactivity Disorder," *Biological Psychiatry*, vol. 63, no. 3, pp. 332–337, Feb. 2008.

[19] A. G. Garrity, G. D. Pearlson, K. McKiernan, D. Lloyd, K. A. Kiehl, and V. D. Calhoun, "Aberrant 'Default Mode' Functional Connectivity in Schizophrenia," *AJP*, vol. 164, no. 3, pp. 450–457, Mar. 2007.

[20] D. P. Kennedy, E. Redcay, and E. Courchesne, "Failing to deactivate: Resting functional abnormalities in autism," *PNAS*, vol. 103, no. 21, pp. 8275–8280, May 2006.

[21] E. Pomarol-Clotet *et al.*, "Failure to deactivate in the prefrontal cortex in schizophrenia: dysfunction of the default mode network?," *Psychological Medicine*, vol. 38, no. 8, pp. 1185–1193, Aug. 2008.

[22] D. K. Binder and C. Steinhäuser, "Functional changes in astroglial cells in epilepsy," *Glia*, vol. 54, no. 5, pp. 358–368, Oct. 2006.

[23] G. Deco, V. K. Jirsa, and A. R. McIntosh, "Emerging concepts for the dynamical organization of resting-state activity in the brain," *Nature Reviews Neuroscience*, vol. 12, no. 1, pp. 43–56, Jan. 2011.

[24] M. Vinck, R. Oostenveld, M. van Wingerden, F. Battaglia, and C. M. A. Pennartz, "An improved index of phase-synchronization for electrophysiological data in the presence of volume-conduction, noise and sample-size bias," *NeuroImage*, vol. 55, no. 4, pp. 1548–1565, Apr. 2011.

[25] M. C. Soriano *et al.*, "Automated Detection of Epileptic Biomarkers in Resting-State Interictal MEG Data," *Front Neuroinform*, vol. 11, Jun. 2017.

[26] E. van Diessen, W. M. Otte, K. P. J. Braun, C. J. Stam, and F. E. Jansen, "Improved Diagnosis in Children with Partial Epilepsy Using a Multivariable Prediction Model Based on EEG Network Characteristics," *PLOS ONE*, vol. 8, no. 4, p. e59764, Apr. 2013.

[27] A. Delorme and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," *Journal of Neuroscience Methods*, vol. 134, no. 1, pp. 9–21, Mar. 2004.

[28] R. Oostenveld, P. Fries, E. Maris, and J.-M. Schoffelen, "FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data," *Comput Intell Neurosci*, vol. 2011, p. 156869, 2011.

[29] P. Jiruska, M. de Curtis, J. G. R. Jefferys, C. A. Schevon, S. J. Schiff, and K. Schindler, "Synchronization and desynchronization in epilepsy: controversies and hypotheses," *J Physiol*, vol. 591, no. Pt 4, pp. 787–797, Feb. 2013.

[30] A. Bhattacharyya, R. B. Pachori, A. Upadhyay, and U. R. Acharya, "Tunable-Q Wavelet Transform Based Multiscale Entropy Measure for Automated Classification of Epileptic EEG Signals," *Applied Sciences*, vol. 7, no. 4, p. 385, Apr. 2017.

[31] M. Sharma, R. B. Pachori, and U. Rajendra Acharya, "A new approach to characterize epileptic seizures using analytic time-frequency flexible wavelet transform and fractal dimension," *Pattern Recognition Letters*, vol. 94, pp. 172–179, Jul. 2017.

[32] A. Sharmila and P. Geethanjali, "DWT Based Detection of Epileptic Seizure From EEG Signals Using Naive Bayes and k-NN Classifiers," *IEEE Access*, vol. 4, pp. 7716–7727, 2016.

[33] P. Swami, T. K. Gandhi, B. K. Panigrahi, M. Tripathi, and S. Anand, "A novel robust diagnostic model to detect seizures in electroencephalography," *Expert Systems with Applications*, vol. 56, pp. 116–130, Sep. 2016.

[34] A. T. Tzallas *et al.*, "Automated Epileptic Seizure Detection Methods: A Review Study," *Epilepsy - Histological, Electroencephalographic and Psychological Aspects*, Feb. 2012.

[35] I. Ullah, M. Hussain, E.-H. Qazi, and H. Aboalsamh, "An automated system for epilepsy detection using EEG brain signals based on deep learning approach," *Expert Systems with Applications*, vol. 107, pp. 61–71, Oct. 2018.

[36] T. Zhang, W. Chen, and M. Li, "AR based quadratic feature extraction in the VMD domain for the automated seizure detection of EEG using random forest classifier," *Biomedical Signal Processing and Control*, vol. 31, pp. 550–559, Jan. 2017.

[37] E. Bokhari and L. Hubert, "The Lack of Cross-Validation Can Lead to Inflated Results and Spurious Conclusions: A Re-Analysis of the MacArthur Violence Risk Assessment Study," *J Classif*, vol. 35, no. 1, pp. 147–171, Apr. 2018.