Chapter

Is EEG a Useful Examination Tool for Diagnosis of Epilepsy and Comorbid Psychiatric Disorders?

Hideki Azuma

Abstract

Diagnosis of epilepsy usually involves interviewing the patients and the individuals who witnessed the seizure. An electroencephalogram (EEG) adds useful information for the diagnosis of epilepsy when epileptic abnormalities emerge. EEG exhibits nonlinearity and weak stationarity. Thus, nonlinear EEG analysis may be useful for clinical application. We examined only about English language studies of nonlinear EEG analysis that compared normal EEG and interictal EEG and reported the accuracy. We identified 60 studies from the public data of Andrzejak 2001 and two studies that did not use the data of Andrzejak 2001. Comorbid psychiatric disorders in patients with epilepsy were not reported in nonlinear EEG analysis except for one case series of comorbid psychotic disorders. Using a variety of feature extraction methods and classifier methods, we concluded that the studies that used the data of Andrzejak 2001 played a valuable role in EEG diagnosis of epilepsy. In the future, according to the evolution of artificial intelligence, deep learning, new nonlinear analysis methods, and the EEG association with the rating scale of the quality of life and psychiatric symptoms, we anticipate that EEG diagnosis of epilepsy, seizures, and comorbid psychiatric disorders in patients with epilepsy will be possible.

Keywords: epilepsy, EEG, diagnosis, nonlinear analysis, comorbid psychiatric disorders

1. Introduction

1.1 EEG and epilepsy

Epileptic seizures usually do not emerge during the consultation. The diagnosis of epilepsy begins with a conversation with the individual and those who witnessed the seizures. [1] An electroencephalogram (EEG) is also used for the diagnosis of epilepsy. The gold standard for diagnosis of epilepsy is simultaneous ictal EEG recording with video, but this method is not applicable for many patients. The presence of epileptic paroxysmal abnormalities can help with the diagnosis. If a non-expert makes the diagnosis based on EEG findings alone rather than seizure symptoms, misinterpretation of the EEG findings may increase the false-positive diagnosis of epilepsy. Many physicians anticipate that EEG diagnosis for epilepsy will become possible with technological advances, even when no EEG abnormalities

are present. EEG is useful not only for diagnosis, but also for monitoring during the course of treatment. [2] Psychiatric disorders occur more frequently as comorbidities in patients with epilepsy [3], and they can affect quality of life. [4]

1.2 EEG and nonlinearity

EEG is characterized by its nonlinearity. [5] Nonlinear dynamics is a concept that includes chaos. Therefore, the adaptation of nonlinear EEG analysis is more useful than that of linear EEG analysis. [6] In nonlinear dynamics, the time series data of EEG can be transformed into a reconstructed state space, which is calculated according to the embedded theorem [7, 8], and the dynamic attractors can be reconstructed. The reconstruction enables us to estimate nonlinear statistics such as fractal dimension and bifurcation structure. The attractor here is a set of trajectories where all of the nearest trajectories converge. [9] CD [9–11], which is a kind of fractal dimension, is a dimension that is occupied by the attractor in phase space. The method of Grassberger et al. is often used. [10] The lyapunov exponent is the degree of exponential separation between orbits, and measures the extent by which nearby points on an attractor diverge or converge with respect to each other while moving along any trajectory of the attractor. [9, 12] If the largest lyapunov exponent is greater than zero, this shows the presence of deterministic chaos. If the lyapunov exponent is less than or equal to zero, this shows a periodic or quasiperiodic motion, respectively. Furthermore, to show the nonlinearity of EEG, generation of surrogate data with linear characteristics and demonstration of a significant difference between them are necessary. In addition, nonlinear analysis is possible with the assumption that EEG exhibits weak stationarity, that the mean and the variance are normally distributed in the evaluated interval, and that no noise is present. [13]

1.3 Epilepsy and nonlinear EEG analysis

Many studies on the nonlinear analysis of EEG and epilepsy have been reported, including reviews concerning ictal EEG detection and machine leaning approaches. [14–16] Ideally, interictal EEG with no paroxysmal abnormalities should be used to diagnose epilepsy and comorbid psychiatric disorders by using computerized analysis rather than expert observation and interpretation.

1.4 Objectives in this review

Therefore, in the present review, we investigated the reports on the nonlinear analysis of EEG between normal and epileptic groups, focusing on the diagnosis of epilepsy and comorbid psychiatric disorders.

2. Methods

2.1 Public data set in Andrzejak 2001

A literature search of Scopus and PubMed was performed. In addition, we identified other relevant literature. We selected only about English language reports that compared normal and epilepsy groups. Many reports used data from Andrzejak 2001. [17] They prepared and used five different data sets, A-E, which each contain 100 single channels from EEG segments of 23.6-sec duration. These segments were

selected and extracted from continuous multichannel EEG recordings after visual inspection for artifacts, e.g., due to muscle activity or eye movements. Set A and set B consisted of EEGs from five healthy volunteers with eyes open and closed, respectively. Set C and set D consisted of EEGs from five patients in the epileptogenic zone (set D) and from the hippocampal formation of the opposite hemisphere of set D (set C). Set E contains ictal activity. Set A and set B were recorded extracranially, whereas set C, set D, and set E were recorded intracranially.

2.2 Nonlinearity of the data set

The objective of the study by Andrzejak 2001 was examination of nonlinearity. They generated 39 surrogate data points from all EEG segments for nonlinear prediction error and CD according to the weak stationarity assumption. Nonlinearity was found except in set A for nonlinear prediction error, but only in set D and set E for CD. They discussed that they cannot rule out the possibility that the surrogate test compared to the surrogate data with linear properties including the weak stationarity may result in a false-positive rejection of nonstationarity, and that the surrogate test has neither high sensitivity nor specificity for nonstationarity in nonlinear dynamics systems. [17] Thuraisingham reexamined the data using MPR complexity and normalized shanon spectral entropy, taking into account the probability distribution function. [18] He carried out a surrogate test using the Amplitude Adjusted Fourier Transform method to generate 1000 surrogate data points for evaluation of entropy and complexity. The degree of nonlinearity was set E > set D > set C > set B > set A. However, when adjusted for the effect of noise, all data showed the same degree of nonlinearity by the above method. Set A showed more nonlinearity than set B, and Thuraisingham concluded that denoising with a wavelet was effective for nonlinearity. In light of these results, we considered all five EEG sets as nonlinear and examined the difference between the normal EEG and interictal EEG among the five EEG sets. There were many studies on the comparison between other sets vs. set E. However, an expert can easily interpret set E as ictal. The diagnosis of epilepsy from interictal EEG with no paroxysmal abnormalities is meaningful for both specialists and non-specialists. Therefore, in this review, in the studies with explicit comparisons with the data set of Andrzejak 2001, A vs. C, A vs. D, AB vs. CD vs. E, A vs. B vs. C vs. D vs. E, B vs. C, B vs. D, A vs. D vs. E, A vs. C vs. E, and AB vs. CD, were examined.

3. Results

3.1 Normal vs. epilepsy

The development of feature extraction with nonlinear analysis methods and machine learning has been reported in studies of various combinations of classifications on EEG diagnosis of epilepsy. (**Table 1**). [19–79] **Table 2** shows the details of the classification. Sixty studies using the Andrzejak 2001 data set were selected, and two studies between normal and epileptic groups were selected. Although set C (the opposite site of the epileptogenic zone) and set D (the site of the epileptogenic zone) were interictal and intracranial EEG, the results for B vs. C (99.3% accuracy) and B vs. D (99.5% accuracy) by Gupta 2018 [29] and the results for A vs. D (100% accuracy) by Kaya 2015 [45] and 2018 [30] and for A vs. C (99.7% and 99.6% accuracy) by Raghu 2017 [36] and Liu 2020 [21] were reported. The feature extraction methods and the classifiers were different in each study. Nevertheless,

Author (year) [reference number]	**Feature extraction**	**Classifiers**	**Comparisons [accuracy%]**
Gao (2020) [19]	ApEn, RQA	CNN, BRBP	AB vs. CDE [99.2]
Goshvarpour (2020) [20]	PP	KNN, PNN	A vs. D vs. E [98.3]
Liu (2020) [21]	WPE, WEE, TEE, PSD, 1D-LBP, LNDP, 1D-LGP, LSP, SampEn, LSPA, NEO, HSFV*	AB*, NB, DA, KNN, SVM	A vs. D vs. E [99.0], AB vs. CD vs. E [98.1], AB vs. CD [99], A vs. D [99.5], A vs. C [98.6], B vs. C [99.6], B vs. D [99.6], A vs. CD [98.8], B vs. CD [99.1]
Abedin (2019) [22]	Multilevel DWT	Nonlinear ANN	A vs. D vs. E [97.3]
Fasil (2019) [23]	ExpEn	SVM	A vs. D vs. E [89], A vs. C vs. E [91.6]
Ghayab (2019) [24]	TQWT	KNN*, SVM, BT	AB vs. CD vs. E [100], A vs. B vs. C vs. D vs. E [100]
Kaur (2019) [25]	DWT	BSVM	A vs. C [76], B vs. C [81.6], A vs. D [72.8], B vs. D [71.1]
Sun (2019) [26]	ESN, AR	ELM	A vs. D vs. E [98.3]
Torse (2019) [27]	RP, RQA	SVM*, ANN, PNN	AB vs. CD vs. E [91.2]
Tuncer (2019) [28]	LSP	LDA-SVM*, QDA, KNN	A vs. D vs. E [98.6], A vs. B vs. C vs. D vs. E [93], A vs. D [99.5]
Gupta (2018) [29]	DCT, HE, ARMA	SVM	A vs. C [96.5], A vs. D [98.4], B vs. C [99.3], B vs. D [99.5], AB vs. CD [97.7]
Kaya (2018) [30]	1D-TP (1; lower features, 2; upper features)	ANN*, RF†, FT‡, SVM, BayesNet	1; A vs. D vs. E [95.7]†, A vs. D [99]*, 2; A vs. D vs. E [94] †, A vs. D [100]†,‡,
Sairamya (2018) [31]	LNGP†, SWLNGP‡	ANN*, KNN, QLDA, SVM	A vs. D vs. E [99.7] † [99.6] ‡, AB vs. CD vs. E [99.5] † [99.3] ‡, A vs. D [99.9] †, [99.9] ‡
Zhang (2018) [32]	fDistEn, WPD	KNN*, Kruskal-Wallis, nonparametric ANOVA	A vs. D vs. E [99.3], A vs. B vs. C vs. D vs. E [76]
Abdulhay (2017) [33]	ApEn, SampEn, PE, HE, HFD, HOS	KNN, SVM, NB	A vs. D vs. E [98.5]
Jaiswal (2017) [34]	1D-LBP†, LNDP‡, 1D-LGP	ANN*, NN, SVM, DT	A vs. D vs. E [97.0] † [98.2] ‡, A vs. D [99.3] †[99.9] ‡
Kalbkhani (2017) [35]	ST, KPCA	NN	A vs. D vs. E [99.3], AB vs. CD vs. E [99.5], A vs. C vs. E [99.9]
Raghu (2017) [36]	WPD, LEEn*, NE†	REN	A vs. C [99.7]*, [99.3] †
Tiwari (2017) [37]	LBP	SVM	AB vs. CD vs. E [98.8]
Wang (2017) [38]	LDWT	NSVM	A vs. D vs. E [98.4]
Wen (2017) [39]	GAFDS, SampEn, HE, LE, MFDFA	KNN*, LDA, DT, AB, MLP, NB	A vs. D vs. E [97.3]
Zhang (2017) [40]	LMD, RE, HE	GASVM*, BPNN, KNN, LDA, SVM	AB s CD vs. E [98.4]
Hekim (2016) [41]	DWT, EWD, EFD, SE	ANFIS	AB vs. CD [96.5]

Author (year) [reference number]	Feature extraction	Classifiers	Comparisons [accuracy%]
Murugavel (2016) [42]	LLE, ApEn, DWT	H-MSVM*, ANN	A vs. D vs. E [96], AB vs. CD vs. E [95], A vs. B vs. C vs. D vs. E [94]
Peker (2016) [43]	DTCWT	CVANN	A vs. D vs. E [99.3], AB vs. CD vs. E [98.2]
Abalsaud (2015) [44]	DCT, DWT	NSC*, ANN, NB, KNN, SVM	A vs. C vs. E [90]
Kaya (2015) [45]	1D-LBP	GRA	A vs. D [100]
Martis (2015) [46]	DWT, LLE, HFD, HE, SampEn	RBFSVM*, LSVM, PSVM, QSVM, DT, KNN	A vs. D vs. E [98]*
Riaz (2015) [47]	EMD	SVM*, DT, KNN, ANN	A vs. D vs. E [91], A vs. B vs. C vs. D vs. E [94]
Tawfik (2015) [48]	WPE, DWT	LSVM*, NSVM†, ANN	A vs. D vs. E [97.2]* [97.5] †, A vs. B vs. C vs. D vs. E [91.6]* [93.7] †
Kaya (2014) [49]	LBP, 1DLBP	BayesNet*, SVM, ANN, LR, FT	A vs. D vs. E [95.6], A vs. D [95.5]
Sivasankari (2014) [50]	ICA, STFT, CD, LE	FFBPNN*, ANFIS	A vs. D vs. E [100], A vs. B vs. C vs. D vs. E [96.2]
Acharya (2013) [51]	CWT, HOS, CM, RLM, LBP, LME	SVM*, ANOVA, DT, KNN, PNN	AB vs. CD vs. E [96]
Alam (2013) [52]	EMD	ANN	A vs. D vs. E [100], AB vs. CD vs. E [80]
Fernández-Blanco (2013) [53]	GP		A vs. D vs. E [98.5], AB vs. CD vs. E [97.8]
Hosseini (2013) [54]	HE, LLE	ANFIS	AB vs. CD [97.4]
Niknazar (2013) [55]	RQA, DWT	ECOC	AB vs. CD vs. E [98.6]
Peker (2013) [56]	FCBFA	CVANN	A vs. D vs. E [97]
Seng (2013) [57]	HE, FD, ApEn, LLE, CD	RBFSVM	AB vs. CD vs. E [97.1]
Wang (2013) [58]	BD, FI	SVM	A vs. D vs. E [97.1]
Zhu (2013) [59]	SampEn	MKM*, KMA, SVM	A vs. C [95], A vs. D [96]
Acharya (2012) [60]	ApEn, SampEn, FD, HOS, HE	FSC*, DT, GMM, KNN, RBFSVM, PNN	A vs. D vs. E [99.7]
Acharya (2012–2) [61]	DWT(23.6 sec), ICA	RBFSVM*, DT, KNN, PNN, FSC, GMM	A vs. D vs. E [96]
Martis (2012) [62]	EMD	DT*, ANOVA	A vs. D vs. E [95.3]
Acharya (2011) [63]	RP, RQA	SVM*, GMM, FSC, KNN, NB, DT, PNN	A vs. D vs. E [94.4]
Guo (2011) [64]	DWT, GP	KNN	A vs. D vs. E [93.5]
Mhandoost (2011) [65]	DWT	GARCH*, MRF	A vs. D vs. E [98.8], A vs. C vs. E [98]
Orhan (2011) [66]	DWT	MLP-NN*, KMC	A vs. D vs. E [96.6]

Author (year) [reference number]	Feature extraction	Classifiers	Comparisons [accuracy%]
Ballli (2010) [67]	HOA, TRA, ApEn, LLE, CD, NPE, HE, AR	SFFS-LDA	A vs. B vs. C vs. D vs. E [81.4]
Liang (2010) [68]	ApEn, AR, GA, PCA	RBFSVM*, LLS, LDA, BPNN, LISVM	A vs. D vs. E [98.6], A vs. B vs. C vs. D vs. E [85.9]
Song (2010) [69]	SmpEn	ELM*, BPNN	A vs. D vs. E [95.6]
Acharya (2009) [70]	CD, HE, ApEn, LLE	GMM*, SVM	AB vs. CD vs. E [95]
Übeyli (2009) [71]	DWT	MLP + LMA NN	A vs. D vs. E [94.8]
Übeyli (2008) [72]	DWT	ME*, EMA, MLP-NN	A vs. D vs. E [93.1]
Gūler (2007) [73]	DWT, LE	RBFSVM*, MLP-NN, PNN, MSVM	A vs. B vs. C vs. D vs. E [99.2]
Tzallas (2007) [74]	STFT, PSD	FFANN	A vs. D vs. E [100], A vs. B vs. C vs. D vs. E [89]
Tzallas (2007–2) [75]	SPWVD	FFANN, PCA	A vs. D vs. E [99.2], AB vs. CD vs. E [97.7]
Übeyli (2007) [76]	PM, MUSIC, MN, PSD	MME *, ME	A vs. B vs. C vs. D vs. E [98.6]
Sadati (2006) [77]	DWT	ANFN*, ANFIS, RBFSVM, FFBPNN	A vs. D vs. E [85.9]
Gūler (2005) [78]	LE, LMA	RNN	A vs. D vs. E [96.7]
Gūler (2005–2) [79]	DWT	ANFIS*, BP, GDM, LLS	A vs. B vs. C vs. D vs. E [98.6]

Accuracy = (TP+ TN)/(TP + FP+ TN+ FN); TP, TN, FP and FN mean true positive, true negative, false positive and false negative, respectively.
*, †, ‡*The accuracy corresponds to each feature extraction and classifier with the symbol.*

Table 1.
Results for the data of Andrzejak 2001.

Comparisons	Mean(SD) [range]	Number of results
A vs. D vs. E	96.8(2.9) [85.9–100]	44 results in 40 studies
A vs. B vs. C vs. D vs. E	92.2(6.7) [76–100]	14 results in 13 studies
AB vs. CD vs. E	96.3(4.9) [80–100]	15 results in 14 studies
A vs. C vs. E	94.8(4.1) [90–99.9]	4 results in 4 studies
AB vs. CD	97.6(0.8) [96.5–99]	4 results in 4 studies
A vs. D	96.7(7.3) [72.8–100]	12 results in 10 studies
A vs. C	94.1(8.2) [76–99.7]	6 results in 5 studies
B vs. D	90.0(13.4) [71.1–99.6]	3 results in 3 studies
B vs. C	93.5(8.4) [81.6–99.6]	3 results in 3 studies

Table 2.
The mean (standard deviation) and number of results for each comparison.

these results were clinically interesting and reasonable. Gruszczyńska 2019 (86.8% accuracy) reported that interictal Fp1 EEG and normal Fp1 EEG using the feature extraction of RQA and RP were classified by SVM. [80] No detailed descriptions were provided for the focal side. Jacob 2016 (100% accuracy) reported the classification of interictal EEG and normal EEG. [81] However, no detailed description was provided of EEGs that were artifact free or with no paroxysmal abnormalities.

3.2 Comorbid psychiatric disorders

No literature on nonlinear EEG analysis for the diagnosis of comorbid psychiatric disorders with epilepsy has been published, and we only found a case series with nonlinear analysis of comorbid psychiatric symptoms with epilepsy. [82] Azuma reported that EEG was artifact free and had no paroxysmal abnormalities and that patients including controls had uncontrolled seizures before and after psychosis. SampEn may not only decrease in the right frontal and frontal-anterior temporal regions before psychosis, but it may also increase in the frontal and frontal-temporal regions during psychosis. Further reports about prodromal periods are needed. Several studies and reviews about forced normalization have been published [83, 84], but none have reported nonlinear analysis as well.

4. Discussion

4.1 Normal vs. epilepsy

In studies on Andrzejak 2001 data, comparisons of A or B vs. C and A or B vs. D have increased in recent years (**Table 1**). Set C and set D consist of intracranial EEG. Usually, intracranial EEG is less noisy, but it provides more localized EEG information. [85, 86] Thus, in the future, comparisons using interictal surface EEG data are needed. This review revealed that the studies in **Table 1** using nonlinear feature extraction methods and classifier methods play a valuable role on EEG diagnosis for epilepsy (A or B vs. C (93.8% accuracy) and A or B vs. D (93.4% accuracy). These results can be further examined in future studies. Thus, consideration and examination with denoising with wavelets [18] and the date of EEG and seizures [87] in nonlinear EEG analysis may be needed in future studies.

4.2 Comorbid psychiatric disorders

In many studies on the diagnosis of depression and schizophrenia [88–97], the nonlinear EEG analysis have been reported, but no nonlinear EEG analysis with accuracy has been reported for comorbid psychotic disorders and depression in patients with epilepsy. Psychiatric comorbidities are common in patients with epilepsy [3], and associations for psychosis with the age at onset, duration of epilepsy, and seizure frequency have been reported. [98, 99] Prodromal symptoms should also be considered when evaluating the onset of psychiatric symptoms. [100] Nonlinear EEG analysis of patients with schizophrenia and depression have been reported, but no nonlinear EEG analysis with accuracy has been reported for comorbid psychotic disorders and depression in patients with epilepsy. No study on forced normalization has been reported using nonlinear EEG analysis. Because psychiatric symptoms affect quality of life in patients with epilepsy [4], we expect that the studies of the association between nonlinear EEG analysis, cognitive function [101–103] and the psychiatric rating scales [104, 105] in the future.

5. Conclusion

EEG exhibits nonlinearity and weak stationarity. Thus, nonlinear EEG analysis is useful to investigate the clinical application for epilepsy, as shown in studies using the public record of Andrzejak 2001. We reviewed the studies using this data set. Using a variety of feature extraction methods and classifier methods, we conclude that these studies played a valuable role in EEG diagnosis for epilepsy. Comorbid psychiatric disorders in patients with epilepsy have not been reported in nonlinear EEG analysis except for one case series of comorbid psychotic disorders. In the future, according to the evolution of artificial intelligence, deep learning, new nonlinear analysis, and the association with the rating scale of the quality of life and psychiatric symptoms, we anticipate that EEG diagnosis for epilepsy, seizures, and comorbid psychiatric disorders in patients with epilepsy will become possible.

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Conflict of interest

None of the authors has any conflict of interest to disclose.

Abbreviations

A

AB; AdaBoost, ANFIS; Adaptive neuro-fuzzy inference system, ANFN; Adaptive neural fuzzy network, ANN; Artificial Neural Network, ApEn; Approximate entropy, AR; Autoregressive model, ARMA; Autoregressive moving average model.

B

BayesNet; Bayes networks; BD; Blancket dimension, BP; Backpropagation, BPNN; Back propagation neural network, BRBP; Bayesian regularization back-propagation, BSVM; Bagged support vector machine, BT; Bagging tree.

C

CD; Correlation dimension, CM; Co-occurrence matrix, CNN; Convolutional neural network, CVANN; Complex-valued neural networks, CWPS; Continuous wavelet power spectra, CWT; Continuous wavelet transform.

D

DA; Discriminant analysis, DCT; Discrete cosine transform, DT; Decision tree, DTCWT; Dual-tree complex wavelet transformation, DWPS; Discrete wavelet power spectra, DWT; Discrete wavelet transform.

E

ECOC; Error-correction output codes, EFD; Equal frequency discretization, ELM; Extreme learning machine, EMA; Expectation–maximization algorithm, EMD; Empirical Mode Decomposition, ENSC; Ensemble noise-aware signal combination; ESN; Echo state network, EWD; Equal width discretization, ExpEn; Exponential energy.

F

FCBFA; Fast Correlation Based Filter algorithm, FD; Fractal dimension, fDistEn; Fuzzy distribution entropy, FE; Fuzzy entropy, FFANN; Feed-forward

artificial neural network, FFBPNN; Feed forward back-propagation neural network, FI; Fractal intercept, FPCA; Functional principal component analysis, FSC; Fuzzy Sugeno Classifier, FT; Functional trees.

G

GA; Genetic algorithm, GAFDS; Genetic algorithm-based frequency-domain feature search, GASVM; Genetic algorithm support vector machine, GARCH; Generalized autoregressive conditional heteroscedasticity, GDM; Gradient descent method, GEO; Gradient energy operator, GMM; Gaussian mixture model, GP; Genetic programming, GRA; Gray relational analysis.

H

HE; Hurst exponent, HFD; Higuchi fractal dimension, H-MSVM; Hierarchical multi-class support vector machine, HOA; Higher order autocovariance, HOS; Higher order spectra, HSFV; Hybrid-selection-feature vector.

I

ICA; Independent component analysis, ICNC; Inverse correlation network coupling, IShE; Indirect shannon entropy.

K

KMA; K-means algorithm, KMC; K-means clustering, KNN; K-nearest neighbor, KPCA; Kernel principal component analysis, KSE; Kolmogorov Sinai entropy.

L

LE; Lyapunov exponent, LBP; Local binary pattern, LEEn; Log energy entropy, LDA; Linear discriminant analysis, LLS; Linear least squares, LMA; Levenberg–marquardt algorithm, LMD; Local mean decomposition, LME; Laws mask energy, LNDP; Local neighbor descriptive pattern, LNGP; Local neighbor gradient pattern, LR; Logistic regression, LSP; Local speed pattern, LSP; Local senary pattern, LSPA; Lorenz scatter plot area, LS-SVM; Last squares support vector machine, LSVM; Linear support vector machine.

M

ME; Mixture of experts, MFDFA; MKM; Multi-scale K-means algorithm, Multifractal detrended fluctuation analysis, MLP; Multilayer perceptron, MME; Modified mixture of experts, MN; Minimum-Norm, MPE; Multiscale permutation entropy, MPEr; Multiscale permutation renyi entropy, MRF; Markov random field, MSVM; Multiclass support vector machine, MUSIC; Multiple signal classification.

N

NB; Naive Bayes, NE; Norm entropy, NEO; Nonlinear energy operator, NN; Nearest neighbor, NN; Neural network, NPE; Nonlinear prediction error, NSVM; Nonlinear support vector machine.

O

OC; Omega complexity, 1D-LBP; One-dimensional local binary pattern, 1D-LGP; One-dimensional local gradient pattern, 1D-TP; One-dimensional ternary patterns.

P

PCA; Principal component analysis, PE; Permutation entropy, PM; Pisarenko method, PNN; Probabilistic neural network, PP; Poincare plot, PS; Phase synchrony; PSD; Power spectral density, PSVM; Polynominal support vector machine.

Q

QDA; Quadratic discriminant analysis, QLDA; Quadratic linear discriminant analysis, QSVM; Quadratic support vector machine.

R

RBFSVM; Radial basis function support vector machine, RE; Renyi entropy, REN; Recurrent elman neural network, RF; Random trees, RLM; Run length matrix, RNN; Recurrent neural network, RP; Recurrence plots, RQA; Recurrence quantification analysis.

S

SampEn; Sample entropy, SE; Shannon entropy, SELM; Sparse extreme learning machine, SFFS-LDA; Sequential floating forward search with linear discriminant analysis method, SLMC; Spatial linear mode complexity, SSE; Shannon spectral entropy, ST; Stockwell transform, STFT; Short time fourier transform, SPWVD; Smoothed pseudo-wigner-ville distribution, SVM; Support vector machine, SWLNGP; Symmetrically weighted local neighbor gradient pattern.

T

TEE; Temporal energy entropy, TQWT; Tunable Q-factor wavelet transform, TRA; Time reversal asymmetry.

V

VGA; Visibility graph algorithm.

W

WEE; Wavelet energy entropy, WPE; Wavelet packet energy, WPE; Weighted permutation Entropy, WPD; Wavelet packet decomposition.

Author details

Hideki Azuma
Department of Psychiatry and Cognitive-Behavioral Medicine, Nagoya City University Graduate School of Medical Sciences, Mizuho-Cho, Mizuho-Ku, Nagoya, Japan

*Address all correspondence to: azma@med.nagoya-cu.ac.jp

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