StationPlot: A New Non-stationarity Quantification Tool for Detection of Epileptic Seizures

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Introduction

- Electroence phalogram (EEG)

  EEG signal comprises of information related to neurological activities of the brain [1].

- EEG subsets : A, B, C, D, and E

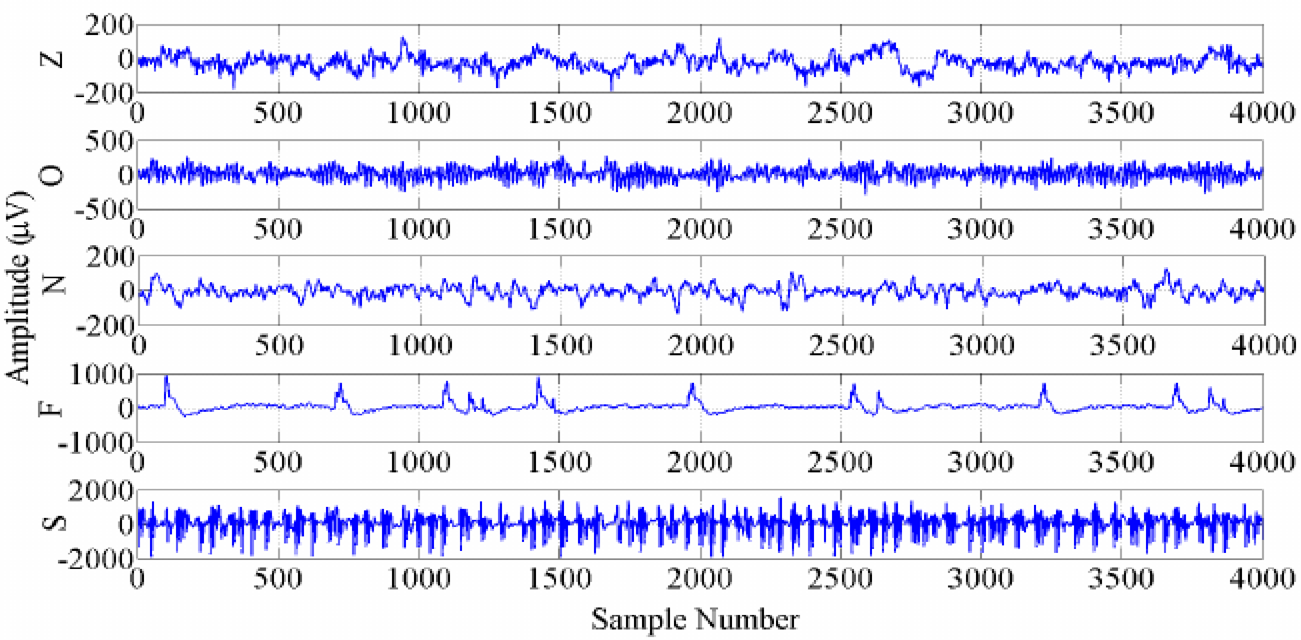

Figure: Represents EEG recoding of subset A, B, C, D, and E

EEG Data for Epileptic Seizure Detection

EEG subsets	Frequency Characteristic	Patient Type
A	173.61 Hz	Healthy
B	173.61 Hz	Healthy
C	173.61 Hz	Non-healthy
D	173.61Hz	Non-healthy
E	173.61Hz	Non-healthy

A: Surface EEG recorded with eyes open.
B: Surface EEG recorded with closed
C: Intracranial recording in seizure-free interval interval of epileptogenic zone
D: Intracranial recording in seizure-free
E: Recorded during ictal period

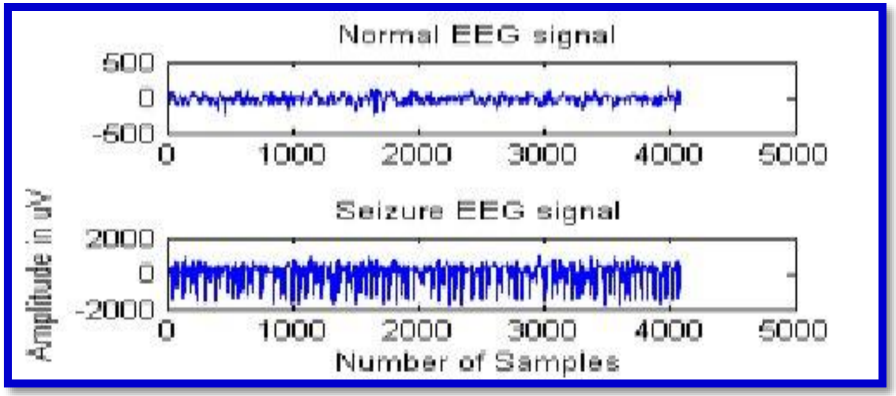

Figure: Represents Normal & Seizure EEG recoding

Ref: http://epileptologiebonn.de/cms/front_content.php?idcat=193&lang=3&changelang=3

EEG Signal Analysis

Importance of EEG Signal

- Diagnostic value in monitoring seizure activity.
- Alteration in signal activity indicates active epilepsy

Reason of Analysis

- Tool to assist doctors in diagnosing active epilepsy patients.
- Improved quality care for patients.

Motivation, Problems and Goals

Motivation	According to WHO, 3.4 million epilepsy patients are registered worldwide with high mortality rate. Shortage of medical professionals, Poor access to diagnostic services and absence of supply chain management [2].
Problems	Interpretation of the neurological activity are subjective. Highly non-stationary complex EEG signal is very difficult to analysis. Additionally, time of seizure can vary which creates more challenge from diagnosis perspective [3-4].
Goals	A novel geometry rich non-stationarity visualization tool for generic time series analysis. EEG signal representation in 2-D space assists in better understanding of seizure activity

Proposed Method for StationPlot

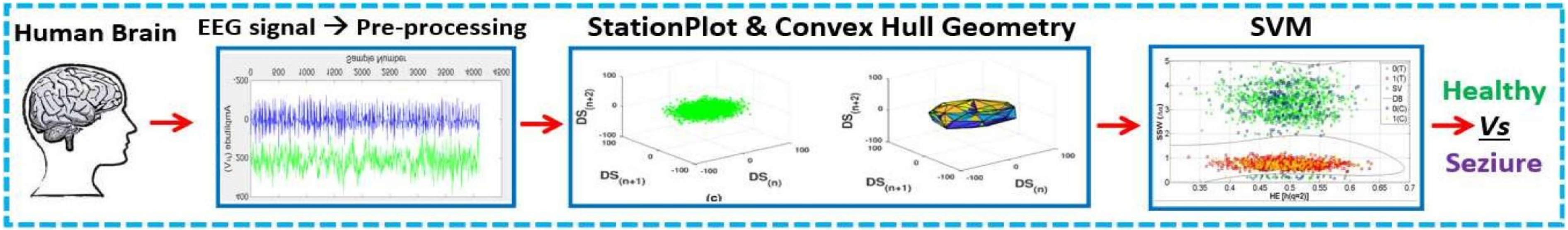

Fig. Pipeline for proposed StationPlot based seizure detection..

Preprocessing:

- Trend-stationary (TS) & Difference stationary (DS) [5].
- Mathematically, Box-Jenkins non-stationary time series analysis for TS & DS.

Feature Extraction & ML Classification

- Feature is extracted from the preprocessed signal via StationPlot & different convex hull geometry (CHG) parameters.
- The extracted features are fed to SVM-RBF for healthy & seizure classification.

2-D StationPlot

Continued…

- The trend present in the given time series, x_t is de-trended by subtracting the mean value or linear trend of the feature vector & a least-squares fit of the time series is envisaged.

- In the Euclidean space, we define the 2-D StationPlot & its subsequent feature extraction thereof.

- For, the 2D-planar case, n^{th} order StationPlot is defined as the plot of $X_1 n$ versus $X_2 n$, where, where,

$$X_1(n) = \Delta^n X(t) \;\&\; X_2(n) = \Delta^{(n+1)} X(t)$$

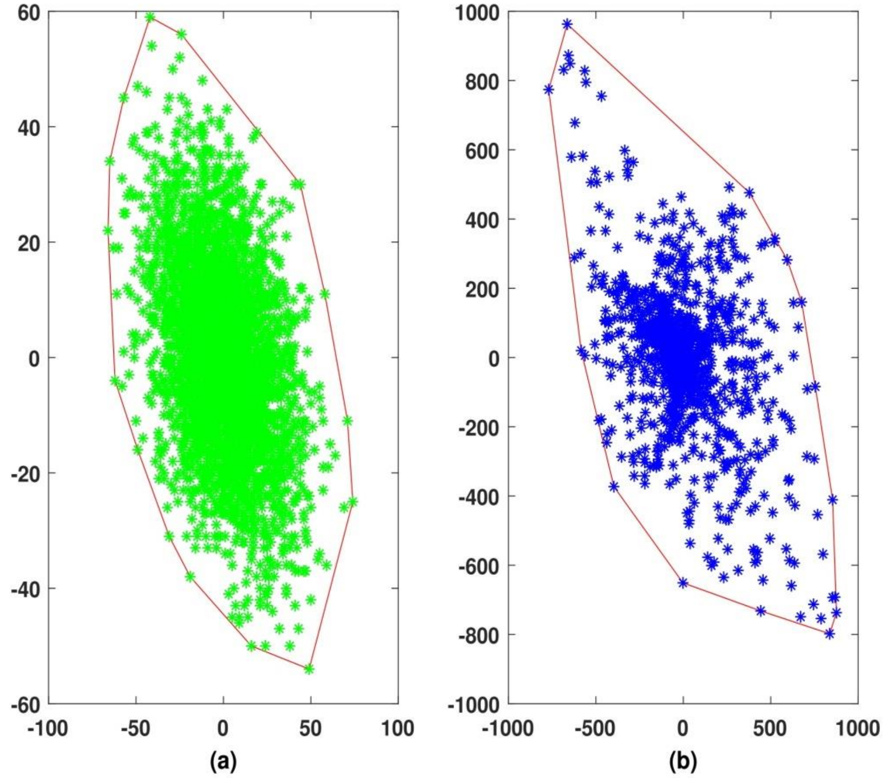

Fig. Representative 2-D StationPlot of (a) Healthy (in green) & (b) Seizure (in blue) EEG signals.

3-D StationPlot

Continued…

- In the Euclidean space, we define the 3-D StationPlot & its subsequent feature extraction thereof.

- For 3D n^{th} order StationPlot is defined as the surface generated by plotting $X_1(n)$, $X_2(n)$ & $X_3(n)$ along the X_1, X_2 and z-axis R^3.

$$X_1(n) = \Delta^n X(t), X_2(n) = \Delta^{(n+1)} X(t) \ \&$$
$$X_3(n) = \Delta^{(n+2)} X(t) \ \&,$$
$$\Delta^n X(t) = \Delta^{(n+1)} X(t) - \Delta^{n-1} X(t-1)$$

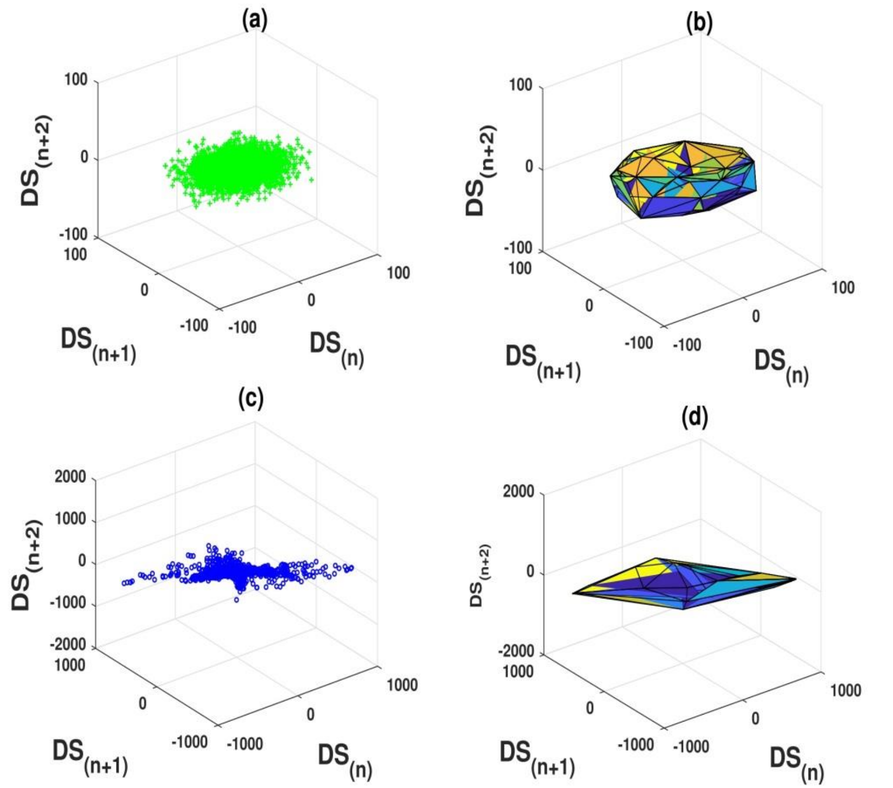

Fig. Representative (a) Healthy EEG signal (in green), (b) 3-D StationPlot of (a), (c) Seizure EEG signal (in blue), (d) 3-D StationPlot of (c)

Convex Hull Geometry on StationPlot

- The convex combination of k number of data-points in X, i.e., x_1, x_2,…, x_3, & with k number of constraints $\theta_1, \dots, \theta_2, \dots \theta_k \geq \theta_1 + \theta_2 + \cdots + \theta_k = 1$ is defined as [6]:

$$x = \theta_1 x_1 + \theta_2 x_2 + \theta_k x_k$$

- CH spans the set of all possible convex combinations of data-points in X by taking all the permutation of the coefficients, θ_k. In the closed form, the convex hull can be expressed as:

$$conv = \left\{ \sum_{i=1}^{|s|} \theta_i x_i \middle| (\forall i: \theta_i \geq 0) \cap \sum_{i=1}^{|s|} \theta_i = 1 \right\}$$

- Quickhull algorithm has been used to compute the CHG [7].

Convex Hull Geometry on StationPlot

Continued…

Convex hull area / volume (CHA/V)

- CHA/V quantifies the polygon area/volume formed by the CH triangulation of the boundary of the CH & signifies the total spread of the ROI on the StationPlot. For x_i, y_i lying on the convex hull in R^2. CH given as [7]:

$$CHA = \frac{1}{2}\left(\begin{vmatrix} x_1 & x_2 \\ y_1 & y_2 \end{vmatrix} + \begin{vmatrix} x_2 & x_3 \\ y_2 & y_3 \end{vmatrix} + \cdots + \begin{vmatrix} x_n & x_1 \\ y_n & y_1 \end{vmatrix}\right)$$

Convex Hull Perimeter (CHP)

- CHP is CH circumference boundary or the aggregate path length of all data point's in the convex combination. It is computed by addition of all the adjoining vertices taken sequentially of the convex hull [7]

$$CHP = \sum_{i=1}^{n} = \left(\sqrt{(x_i - x_{i+1})^2 - (y_i - y_{i+1})^2}\right)$$

Convex Hull Geometry on StationPlot *Continued…*

Circularity (C)

➢ 2D-StationPlot's ROI exhibits asymmetric geometry, which is apprehended by C measuring the degree of roundness of the convex hull & its deviation from its circular nature [6].

$$C = \frac{4 * (CHA) * \pi}{CH^2}$$

Aspect ratio

➢ The aspect ratio measures the ratio of ROI's main inertia axis length, I_{main} to ROI's minor inertia axis length, I_{minor} [7].

$$Aspect\ ratio = \frac{I_{main}}{I_{miror}}$$

Experimental Results & Discussion

- Kruskal-Wallis based ANOVA (Analysis of Variance) test is used for p-value analysis [8].

Features	P-Values	
	A vs E	ABCD vs E
Convex hull geometry (CHG)	**6.75×10^{-16}**	**4.68×10^{-14}**
Convex full perimeter (CHP)	**8.18×10^{-15}**	**3.19×10^{-12}**
Circularity	**6.11×10^{-12}**	**4.02×10^{-10}**
Aspect ratio (AR)	**4.04×10^{-7}**	**1.05×10^{-6}**

Table I: P-values of the extracted features from each modes.

- With **p-values $\leq$ 0.01** for the attributes demonstrate the adequacy of the CHG features
- Features are fed to **SVM-RBF** for classification.

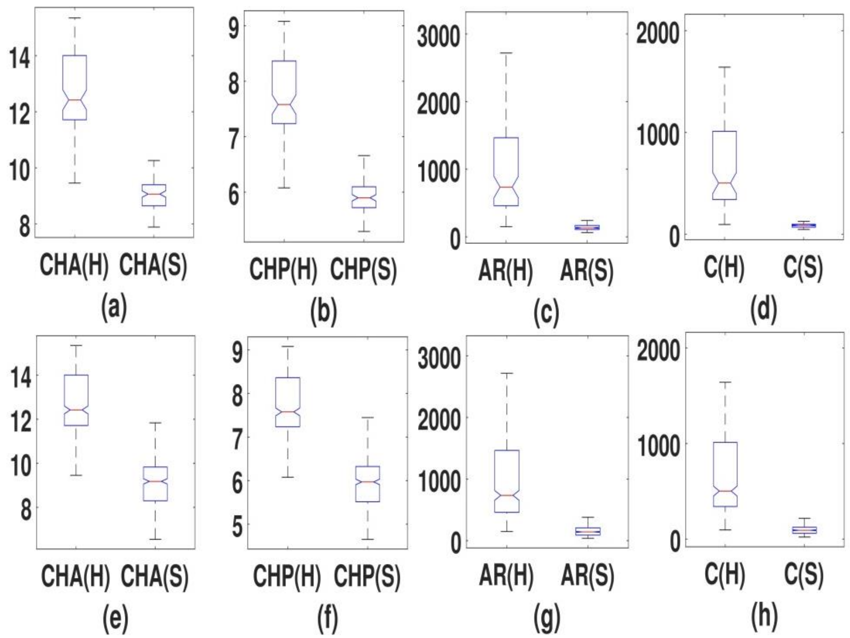

Fig. represents Box-Plot of the extracted CHG features: (a)-(d) for (E vs ABCD) problem & (a)-(d) for (E vs A) problem. **H=Healthy & S=Seizure**

Experimental Results & Discussion

Continued…

Performance Evaluation

- Each of these feature vectors are randomized to eschew the bias of the training parameters & prevent over-fitting. 70% samples are selected for training & the rest 30% is used for testing.
- Standard evolution metrics was utilized for performance evaluation.

$$SN = \frac{TP}{TP + FN},$$

$$SP = \frac{TN}{TN + FP}$$

$$AC = \frac{TP + TN}{TP + TN + FP + FN}$$

Where, TP = true positive, TN = true negative, FP = false positive & FN = false negative respectively.

Experimental Results & Discussion

Continued…

Performance Analysis

Kernel Function (Parameters)	Statistical Parameter	Online Data (Mean ± Std.)	Recorded Data (Mean ± Std.)
Linear	AC	99.31 ± 1.12	98.70 ± 1.68
	SN	99.67± 1.05	**98.74 ± 2.10**
	SP	**97.91 ± 1.79**	96.13 ± 4.12
Quadratic	AC	99.16 ± 1.16	97.66 ± 4.57
	SN	99.46 ± 1.23	98.37 ± 2.19
	SP	96.92 ± 2.01	95.71 ± 6.12
Polynomial (Order = 3)	AC	98.85 ± 1.69	97.46 ± 1.71
	SN	98.96 ± 2.58	98.15 ± 2.24
	SP	97.16± 2.67	**98.57 ± 2.13**
RBF ($\sigma = 2$)	AC	**99.63 ± 1.60**	**98.79 ± 1.66**
	SN	**100 ± 100**	98.18 ± 1.81
	SP	97.35 ± 3.15	93.10 ± 5.48

Table II. Performance Analysis of the Propose Method on the 2-Class problem.

- It can be found that RBF kernel performs significantly better as compared to the other kernels
- An overall classification accuracy of **99.31%** for **(A vs E)** & **98.79%** for **(ABCD vs E)** 2-class problem.
- StationPlot is superior than intensive computational deep learning methods like CNN & RNN.

Seizure detection results of the proposed & state-of-art methods for two-class problem (A vs E), N.A.: Not available.

Ref,.YoP	Methodology + Classifier	Performance(%)		
		AC	SN	SP
[6] (2012)	Discrete wavelet transform (DWT), normalized coefficient of variation (NCOV), LDA.	91.8	83.6	100
[11] (2012)	Permutation Entropy (PE) SVM.	93.8	94.3	93.2
[21] (2013)	Lacunarity & Bayesian linear discriminant analysis (BLDA)	96.6	96.2	96.7
[7] (2014)	Discrete wavelet transform (DWT), fractal dimension (FD), SVM.	97.5	98.0	96.0
[22] (2016)	Weighted-permutation entropy (WPE), SVM.	97.2	94.5	100
[10] (2016)	Multi-level Wavelet Decomposition, ELM.	N.A.	99.4	77.1
This work	**StationPlot, SVM**	**99.6**	**100**	**97.9**

Seizure detection results of the proposed & state-of-art methods for two-class problem (ABCD vs E), N.A.: Not available.

Ref,.YoP	Methodology + Classifier	Performance(%)		
		AC	SN	SP
[3] (2013)	Empirical Mode Decomposition-Modified Peak Selection (EMD-MPS), KNN	98.2	N.A.	N.A.
[4] (2015)	Hilbert marginal spectrum (HMS), SVM	98.8	N.A.	N.A.
[16] (2017)	Local Neighbor Descriptive Pattern (LNDP), One-dimensional Local Gradient Pattern (1D-LGP), ANN	98.7	98.3	98.8
This work	**StationPlot, SVM**	**98.8**	**98.7**	**98.6**

Conclusion and Future Work

- A non-stationarity quantification tool, a.k.a., **StationPlot** for early stage epilepsy detection using EEG signals is presented.
- **StationPlot** can also be used for effective chaos modeling for any non-stationary time series, its visualization & analysis of temporal evolutionary behavior for quantification thereof.
- The D^{th} order differencing statistics exhibits significant knowledge about the underlying system & adequately captures the underlying non-stationarity structure analytics, which is otherwise inaccessible.
- We are escalating our method for noise robustness via inclusion of area moments to study the distribution of non-stationary points.

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