Krig-Detect: Exploring Alternative Kriging Methods for Real-Time Seizure Detection from EEG Signals

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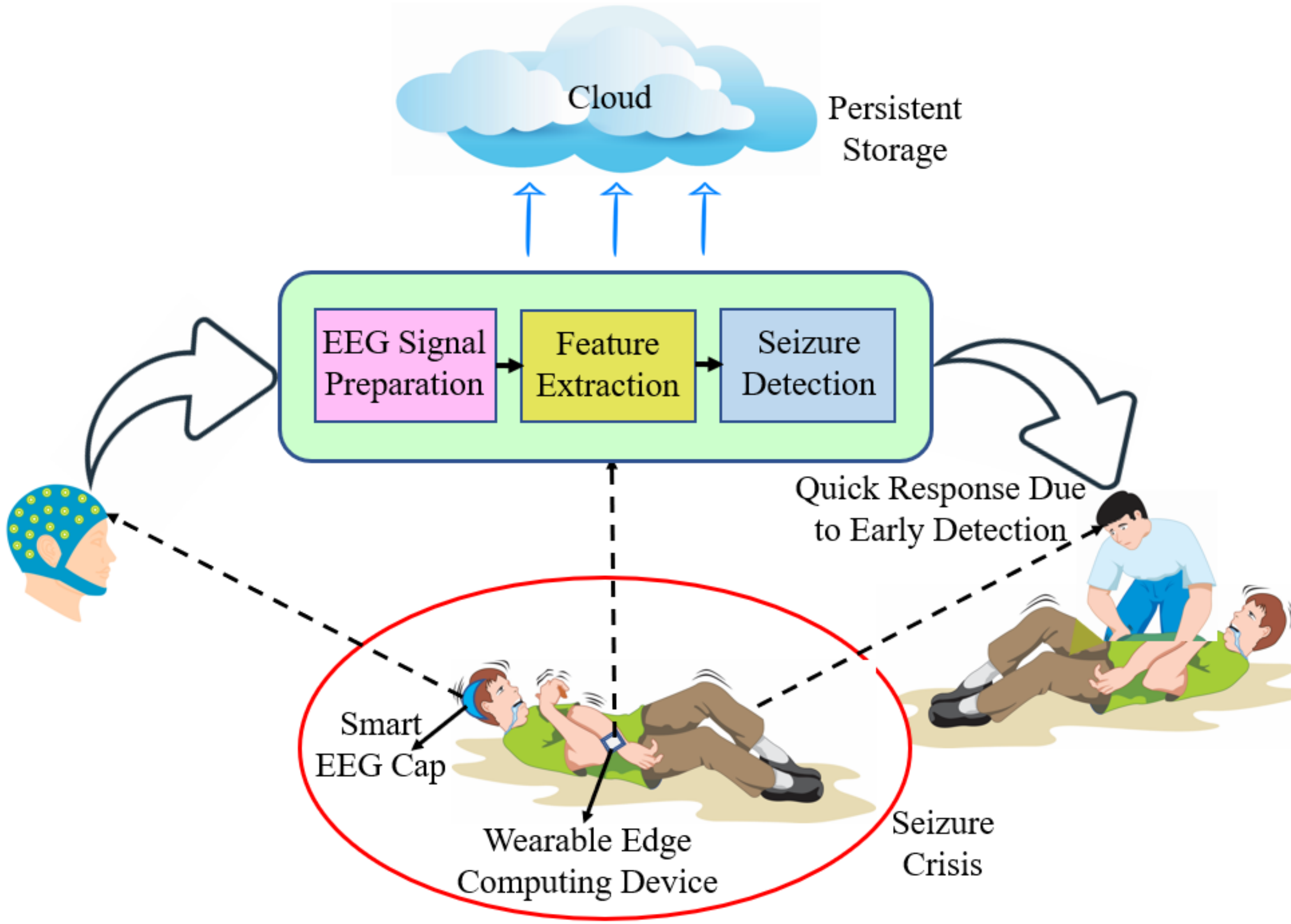
Outline of the talk

- Epileptic Seizures
- Kriging Methods
- Novel Contributions
- Brain as a Spatial Object
- Proposed Seizure Detection Models
- Experimental Results
- Conclusion & Future Research

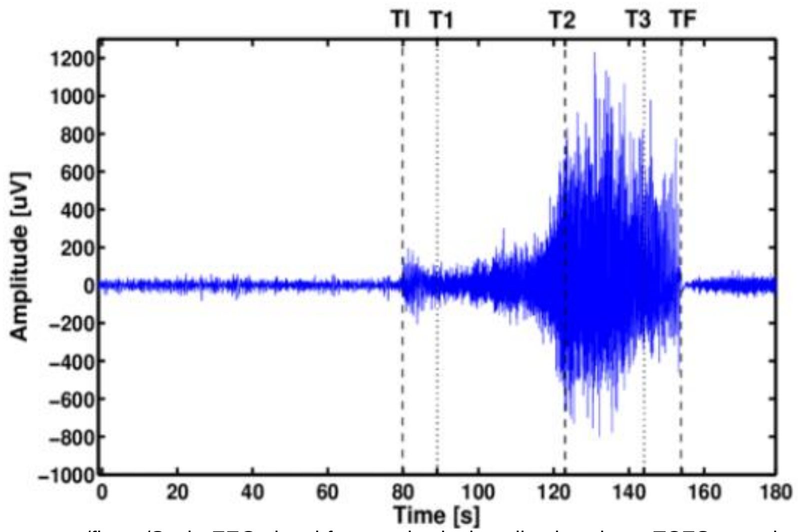
What is Seizure?

- A seizure is an abnormal activity in the nervous system which alters the functioning of the brain and causes victims to lose consciousness and control.

The Research Vision



Characteristics of EEG Signal



Source: https://www.researchgate.net/figure/Scalp-EEG-signal-for-a-tonic-clonic-epileptic-seizure-TCES-recorded-at-the-central_fig2_283645061

- **Complexity**: Highly complex signals depicting the cortical electrical activities in the brain.
- **Intensity**: Low intensity signal measured in µV.
- **Frequency**: Frequency ranges from 0.5–30Hz. Signals are classified as delta, theta, alpha and beta based on frequency.

What are the Research Problems?

- Automatic Seizure Detection.
- Seizure Detection Latency.
- Extended Training Time.
- Patient-Specific Seizure Detection.
- Mobile and Portable Seizure Detection.
- Seizure Crisis Intervention Mechanism.
- Seamless, consistently accurate seizure detection system.
- Low-power seizure detection system.

What are the Challenges?

- Collecting a custom data-set due to the stringent regulations that are involved in collecting data from animals or human subjects.
- The same also applies to testing our models directly on human or animal subjects.
- it is difficult to estimate the level of noise in public data-sets since the conditions of the environment in which they are collected are not known.

Related Research in Seizure Detection – EEG/ML

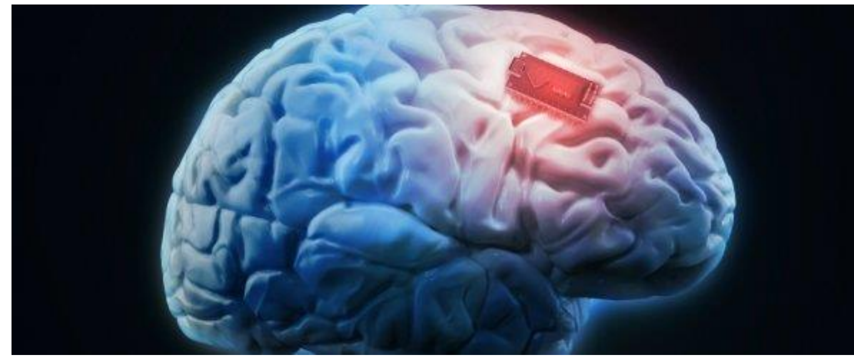
Reference	Dataset	Processing	Classifier Type
Alejandro et al (2017)	CHB-MIT	Time Analysis	Thresholds
Zhou et al. (2012)	Freiburg Database	Wavelet	Bayesian Method
Acharya et al. (2012)	Self-recorded	Freq. Analysis	SVM, KNN
Khan et al. (2012)	Self-recorded	Wavelet	LDA
Runarsson et al (2005)	Self-recorded	Time Analysis	SVM
Rezvan et al. (2017)	Bonn Dataset	Wavelet	MLP
Mursalin et al. (2017)	Bonn Dataset	Time Analysis	Random Forest
Guo et al. (2010)	Bonn Dataset	Wavelet	ANN
Mitra et al. (2009)	Texas' Children	Freq. Analysis	ANN
Zandi et al. (2010)	Vancouver GH	Wavelet	Thresholds

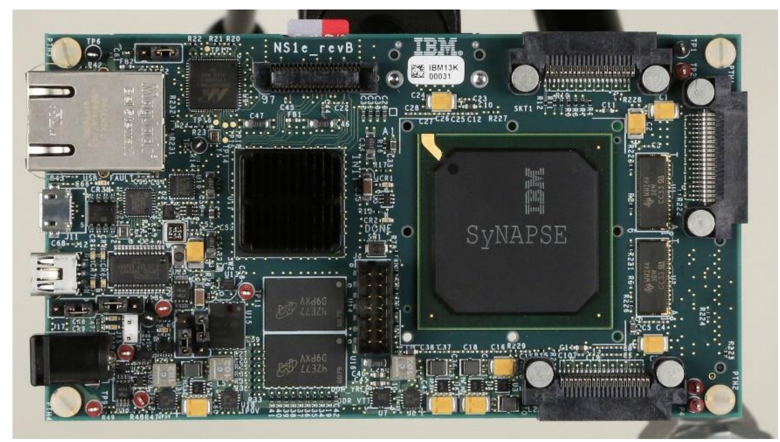
Related Research in Seizure Detection – Non-EEG

- A. Marquez, M. Dunn, J. Ciriaco, and F. Farahmand, “iSeiz: A low-cost real-time seizure detection system utilizing cloud computing,” in Proc. IEEE Glob. Hum. Tech. Conf., 2017, pp. 1–7.
- P. M. Vergara, E. de la Cal, J. R. Villar, V. M. Gonz´alez, and J. Sedano, “An IoT platform for epilepsy monitoring and supervising,” J. Sensors, vol. 2017, July 2017.
- Pavei, J., Heinzen, R. G., Novakova, B., Walz, R., Serra, A. J., Reuber, M., ... & Marques, J. L. (2017). Early seizure detection based on cardiac autonomic regulation dynamics. Frontiers in physiology, 8, 765.
- Jeppesen, J., Fuglsang-Frederiksen, A., Johansen, P., Christensen, J., Wüstenhagen, S., Tankisi, H., ... & Beniczky, S. (2019). Seizure detection based on heart rate variability using a wearable electrocardiography device. Epilepsia, 60(10), 2105-2113.

IBM's Implantable Seizure Detector

- IBM is developing an implantable seizure detector by leveraging on their neurosynaptic computing hardware called TrueNorth.
- The TrueNorth chip is postage stamp-sized and consumes over 1,000 times less power than a conventional processor of similar size.





Source: http://uberveillance.squarespace.com/?category=health_care

Consumer Electronics for Seizure Detection

Source: https://spectrum.ieee.org/the-human-os/biomedical/diagnostics/this-seizuredetecting-smartwatch-could-save-your-life

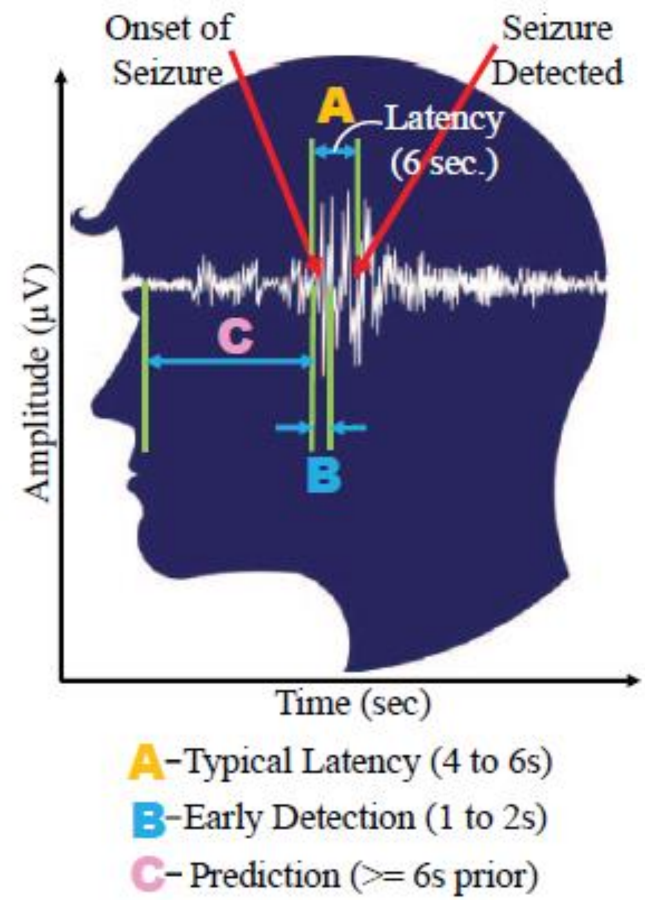
- Embrace2: Smart-band which uses machine learning to detect convulsive Seizures and notifies caregivers.

Source: https://www.empatica.com/embrace2/

- Medical grade smart watch: It detects generalized clonic-tonic Seizures and notifies physicians.

What are the Drawbacks of Existing Works?

- High seizure detection latency.
- Models are complex and unrealistic for real time deployment in the Internet of Medical Things (IoMT).
- Lack of adequate intervention mechanism after detection.



Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Ordinary-Kriging Based Real-Time Seizure Detection in an Edge Computing Paradigm", in Proceedings of the 38th IEEE International Conference on Consumer Electronics (ICCE), 2020, In Press.

Research Question and Hypothesis

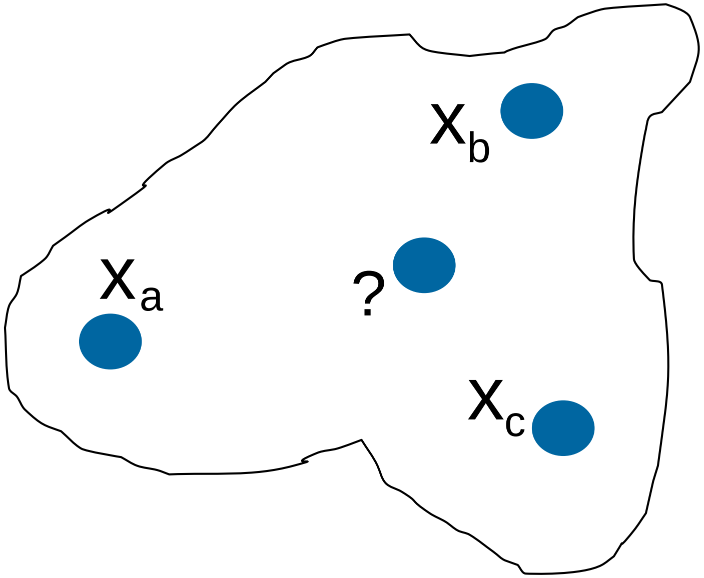
- How effective will Kriging Methods perform on a seizure detection problem given that the brain is structured like a geo map?
- Which Kriging method is best-suited for seizure detection?
- Is it possible to run a seizure detection algorithm on the edge rather than the cloud to achieve a better latency, without significant compromise on accuracy?

Novel Contributions of the Current Paper

- To the best of the authors' knowledge, this is the first work where multiple Kriging methods have been used for real-time seizure detection in an edge computing paradigm.
- A novel achievement of an epileptic seizure detection latency of less than 1 second while maintaining a comparable accuracy with existing models and $O(1)$ time and space complexity for edge computation.

Kriging

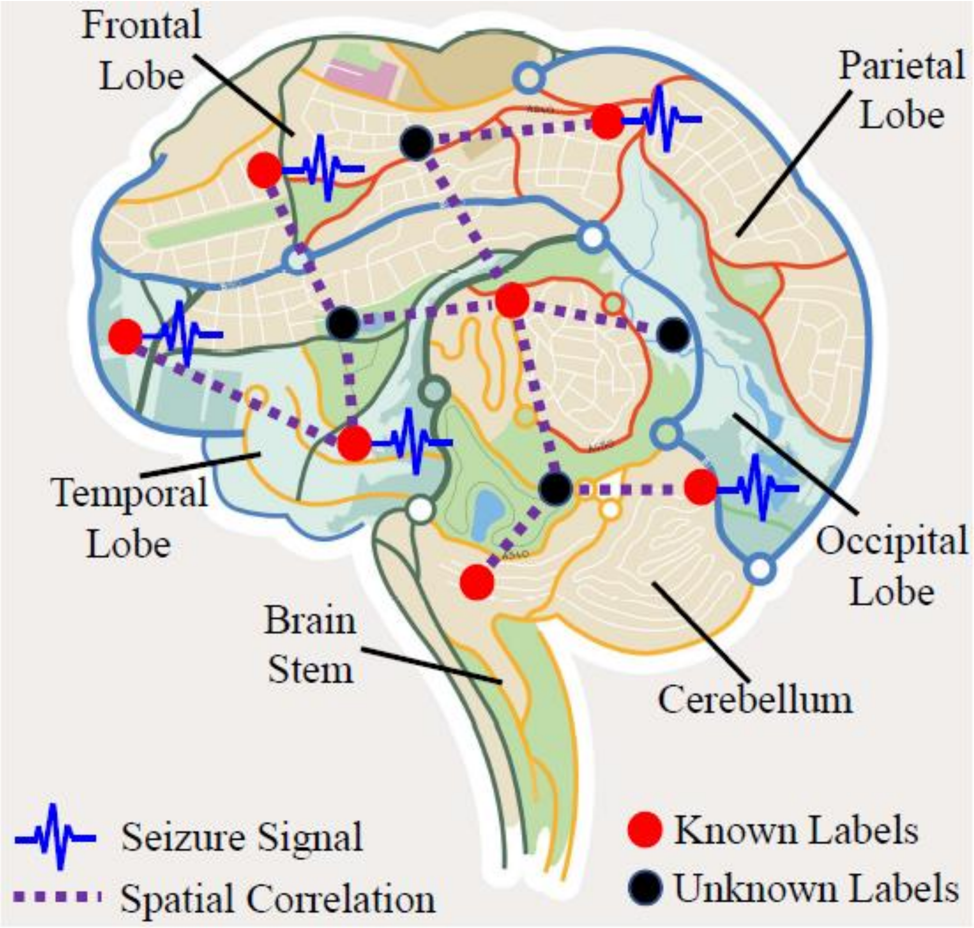
- Kriging was originally developed as a geo-statistical model for spatial prediction.
- It is a stochastic process that is governed by a mean value and the relative co-variances of known data points with respect to an unknown.

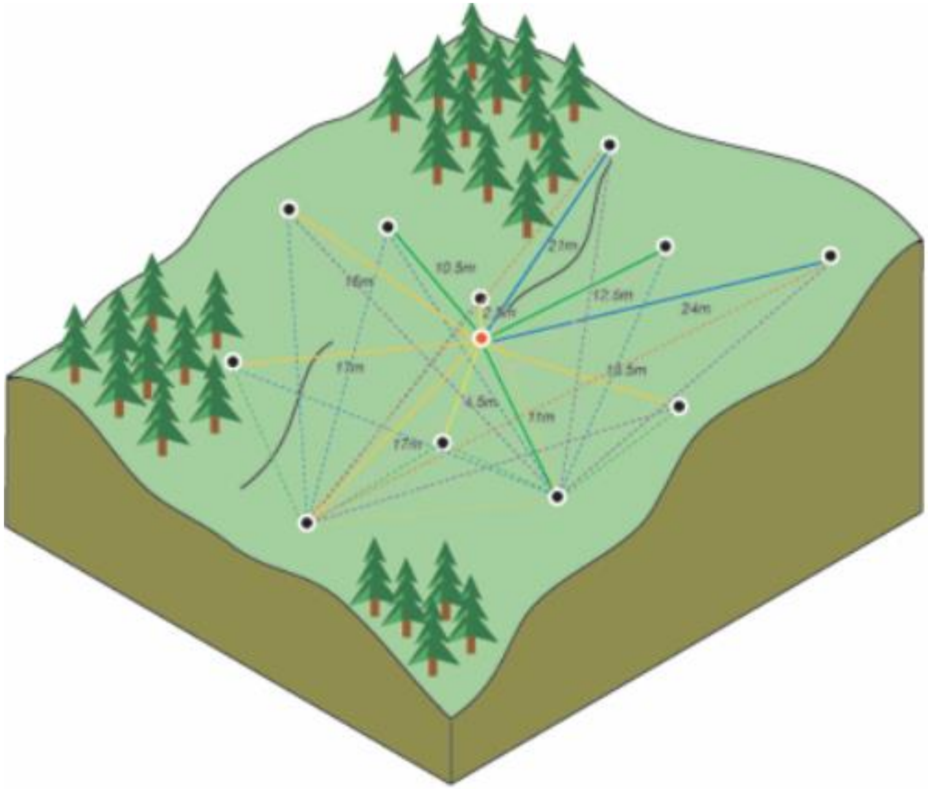


Why Kriging?

- The brain can be modeled as a spatial map on which spatial data processing methods can be applied.
- Kriging method performs very well even on a relatively small dataset unlike machine learning algorithms. This is very important because of the difficulty in obtaining biomedical datasets.
- Kriging model comes with a variance estimate which gives the level of confidence of the model in a given prediction.
- Kriging model is very reliable without requiring the use of many hyperparameters.

Brain as a Spatial Map





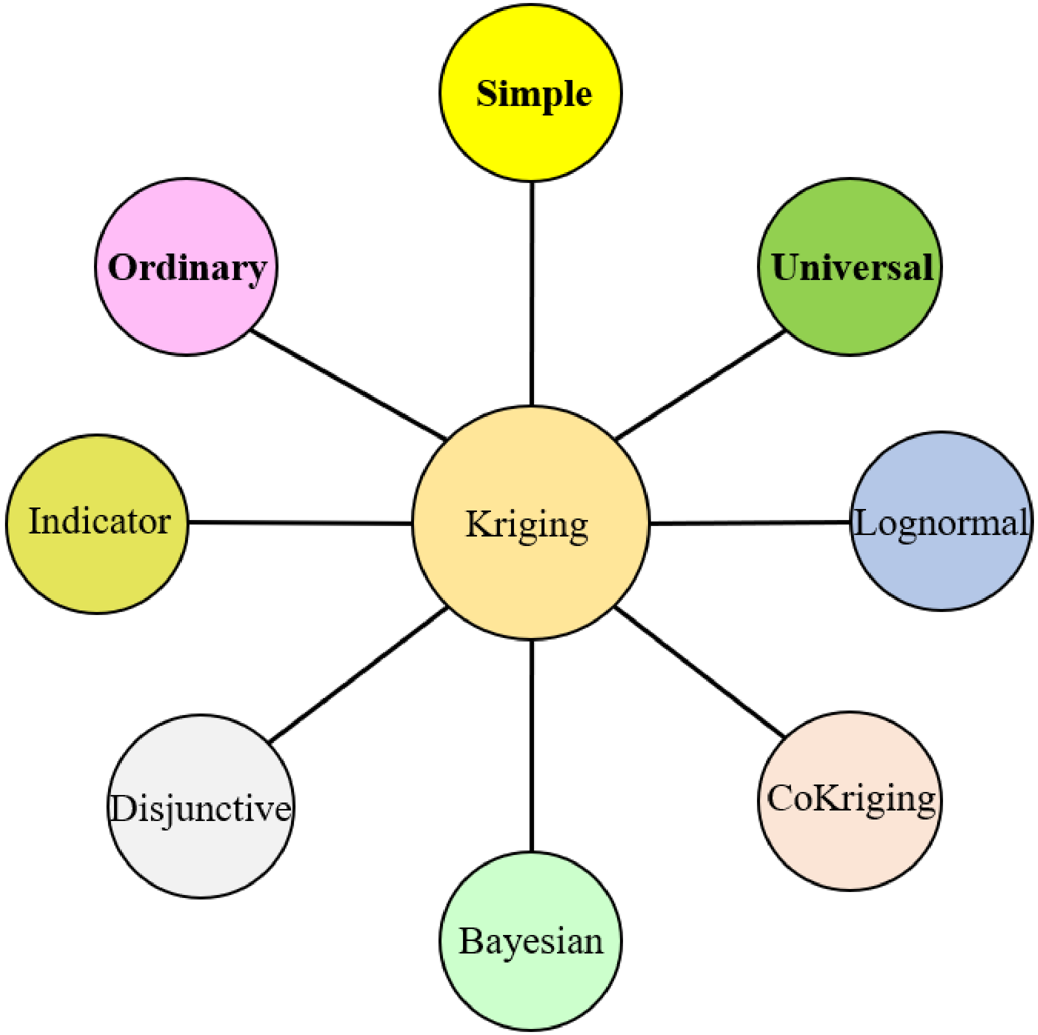
Source:https://desktop.arcgis.com/en/arcmap/10.3/tools/3d-analyst-toolbox/how-kriging-works.htm

Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, “Krig-Detect: Exploring Alternative Kriging Methods for Real-Time Seizure Detection from EEG Signal”, in Proceedings of the 6th IEEE World Forum on Internet of Things (WF-IoT), 2020, pp. Accepted.

Existing Applications of Kriging

- Seismic intensity analysis (De Rubeis et al., 2005).
- Hydrology and well selection (Virdee et al., 1984).
- Geodesy and geology (Reguzzoni et al., 2005).
- Structural reliability (Kaymaz et al., 2005).
- Mixed signal design optimization (Mohanty et al., 2015).
- Cellular network optimization (Braham et al, 2014).

Types of Kriging



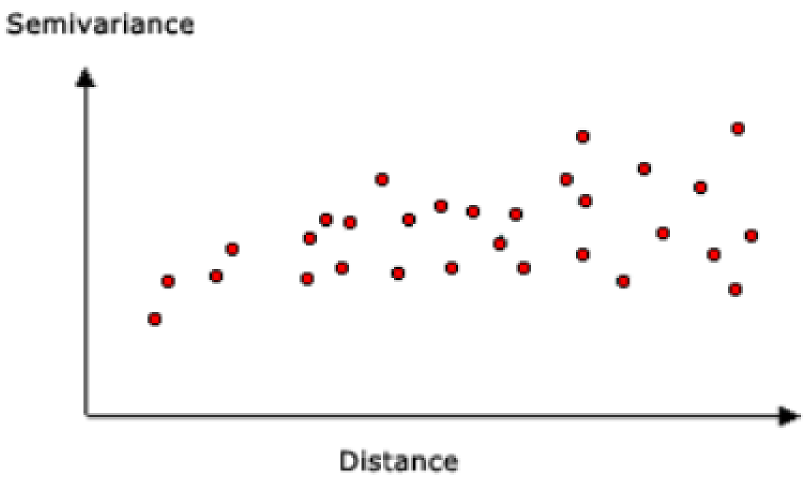
The Kriging Process

- There are three important steps in the application of Kriging methods.
- First is the establishment of spatial continuity through the semi-variogram which is a function of the variations in values over distance.
- Second is fitting a model to the generated semi-variogram.
- The final step is the actual estimation through the fitted model.

The Semi-Variogram

- The semi-variogram is merely a scatter plot with each point representing the average variation among a group of location pairs with common distance known as the lag vector h.
- where ϒ(h) represents the semi-variogram at the lag vector h between two points, N(h) is the number of lag vectors h considered for a single point on the semi-variogram plot.

$$\gamma(\mathrm{h}) = \frac{1}{2\mathrm{N}(\mathrm{h})} \sum_{i=1}^{\mathrm{N}(\mathrm{h})} (\mathrm{Z}(\mathrm{x}_i) - \mathrm{Z}(\mathrm{x}_i + \mathrm{h}))^2,$$



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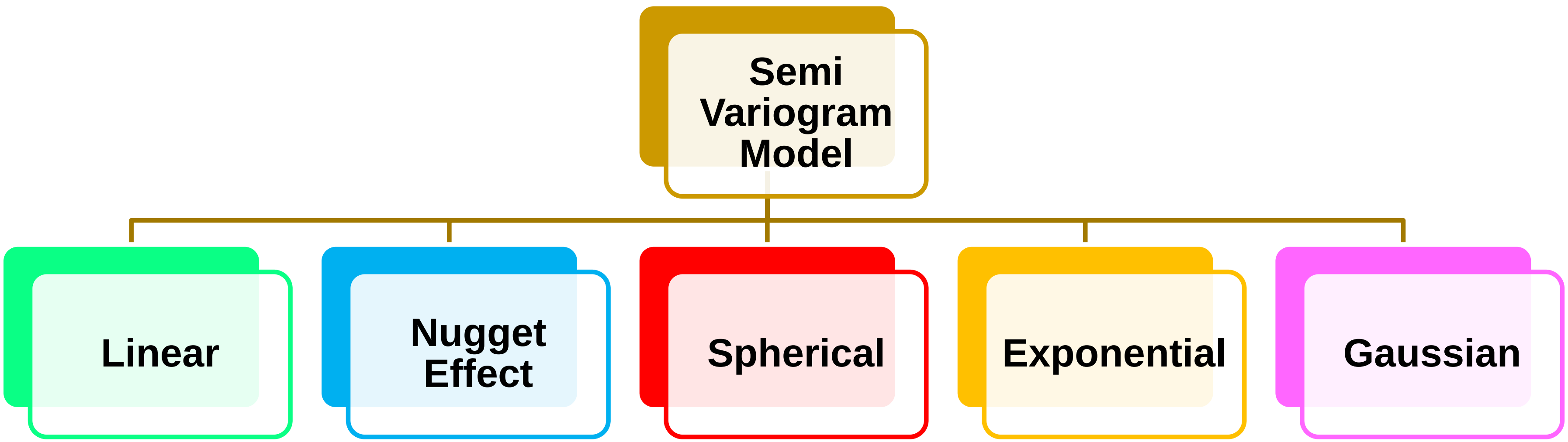
Semi-Variogram Model

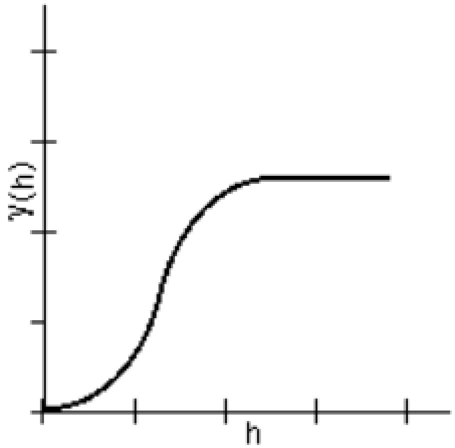
- The semi-variogram model simply fits a line or curve on the scatter plot represented by the semi-variogram.
- There are different types of Semi-Variogram Models as shown below:



Gaussian Semi-Variogram Model

- EEG time-series recorded from normal and epileptic patients were congruent with Gaussian stochastic process. Hence the choice of Gaussian Semi-Variogram Models.

$$\gamma(\mathrm{h}) = \begin{cases} C\left[1 - \exp\left(-\frac{\mathrm{h}^2}{a^2}\right)\right] & \mathrm{h} > 0 \\ 0 & \mathrm{h} = 0 \end{cases}$$



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- C is the sill (total variance contribution) and a is the range (distance on the horizontal axis corresponding to the sill).

Kriging Estimates

- Given the following set of observations $\mathbf{x}_1$, $\mathbf{x}_2$, …, $\mathbf{x}_n$ as inputs, and $y(\mathbf{x}_1)$, $y(\mathbf{x}_2)$, …, $y(\mathbf{x}_n)$ as outputs, the input-output relationship based on Kriging is given by:

$$y(\mathrm{x}_i) = \mu + Z(\mathrm{x}_i),$$

- *W*here i is the data point index, μ is a mean constant and $Z(\mathbf{x}_i)$ is a Gaussian process.
- The weights between the unknown and each of the known can be obtained by solving the following equation, where C(.) is covariance between two points:

$$\sum_{j=1}^{n} \lambda_j \mathrm{C}(\mathrm{x}_i, \mathrm{x}_i) = 2\mathrm{C}(\mathrm{x}_o, \mathrm{x}_i).$$

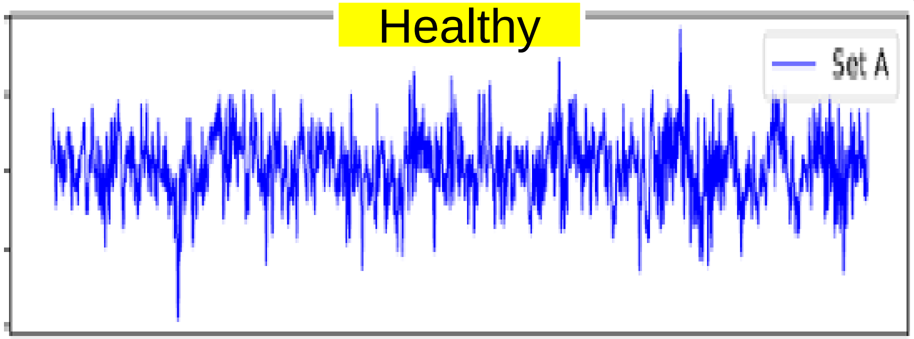
- Hence, the final estimate can be obtained as:

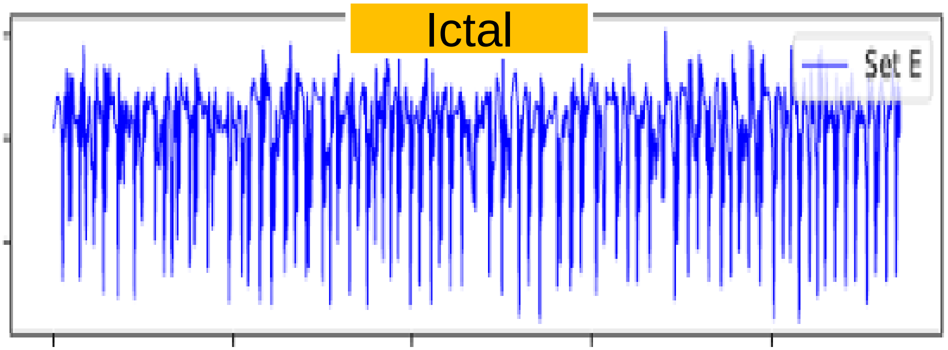
$$y(\mathrm{x}_o) = \sum_{i=1}^{n} \lambda_i Z(\mathrm{x}_i) + (1 - \sum_{i=1}^{n} \lambda_i)\mu_z,$$

Experimental Results - EEG Dataset

BONN DATASET

- The datasets were originally collected from 5 healthy volunteers & five epilepsy patients by the University of Bonn. 5 different sets of data were collected as sets A, B, C,D&E.
- Sets A&B are healthy signals, C&D are inter-ictal signals while E is the only set with ictal signals. Each of the sets comprises 100 EEG segments which were collected with a 128-channel EEG system sampled at 173.61 Hz.

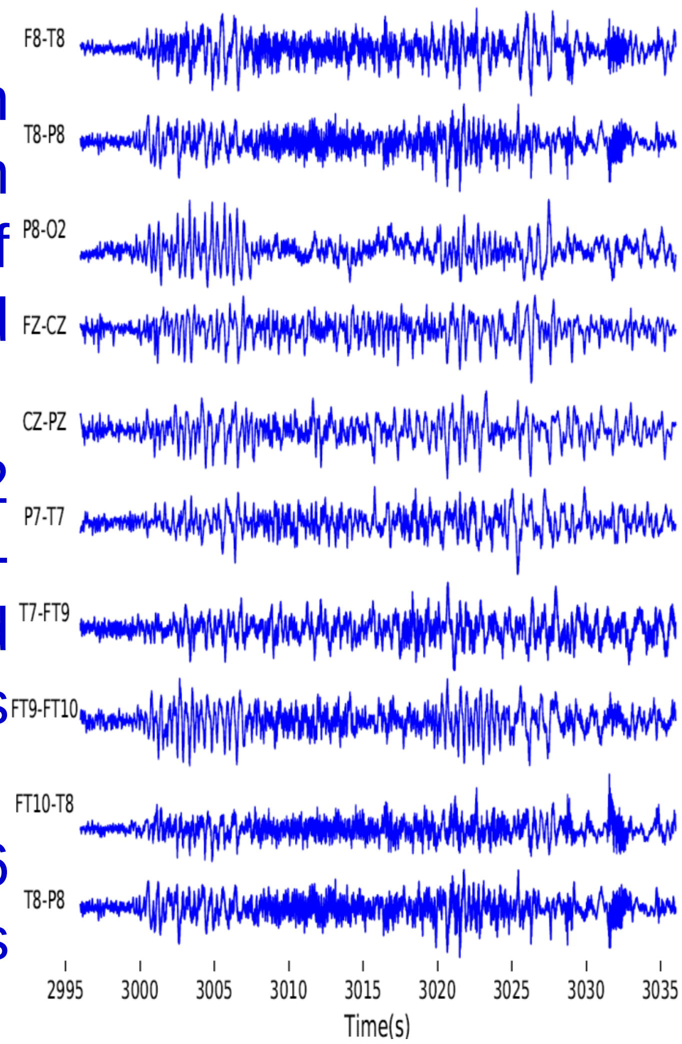




Experimental Results - EEG Dataset

CHB-MIT SCALP EEG DATASET

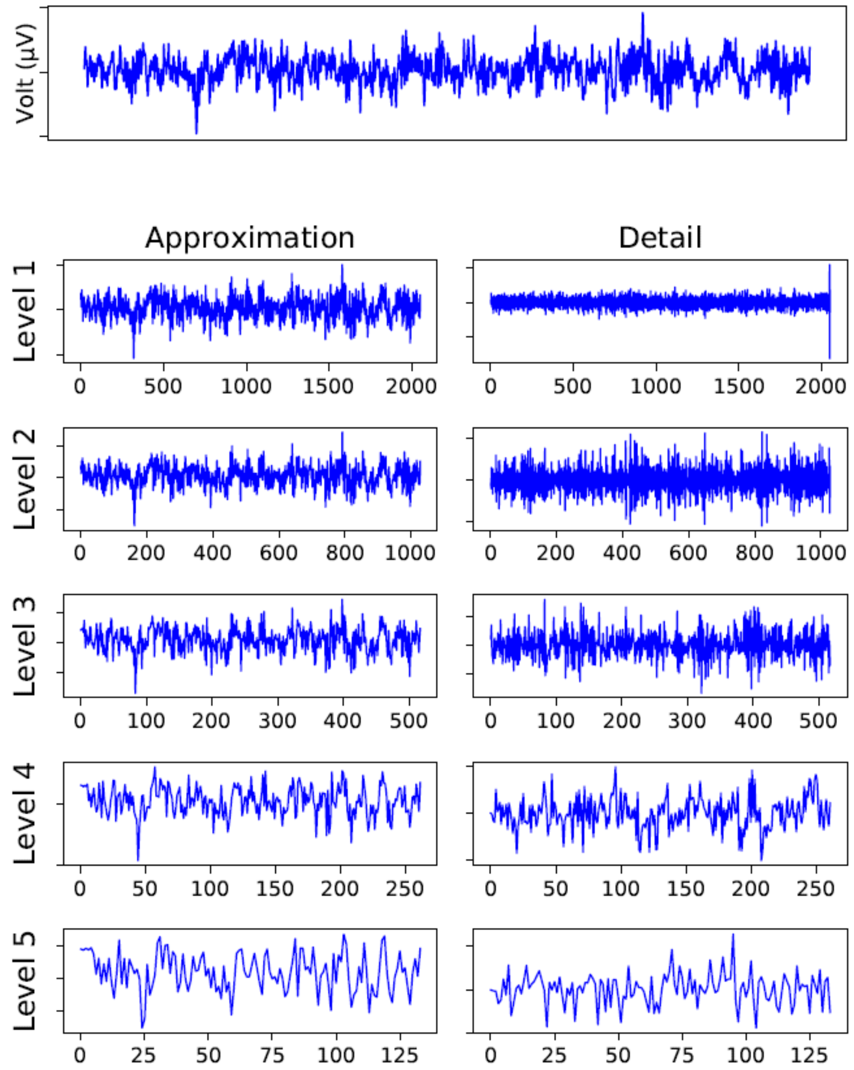
- This dataset was collected at the Children Hospital Boston (CHB) in conjunction with the Massachusetts Institute Of Technology (MIT). It is therefore referred to as the CHB-MIT Scalp EEG Database.
- The EEG signals were collected from 22 epileptic patients of CHB using a 23-channel EEG, sampled at 256Hz and labeled according to the subjects as chb01 to chb23.
- The dataset consists of a total of 916 hours of continuous EEG recordings across all 22 subjects.



EEG Signal Processing

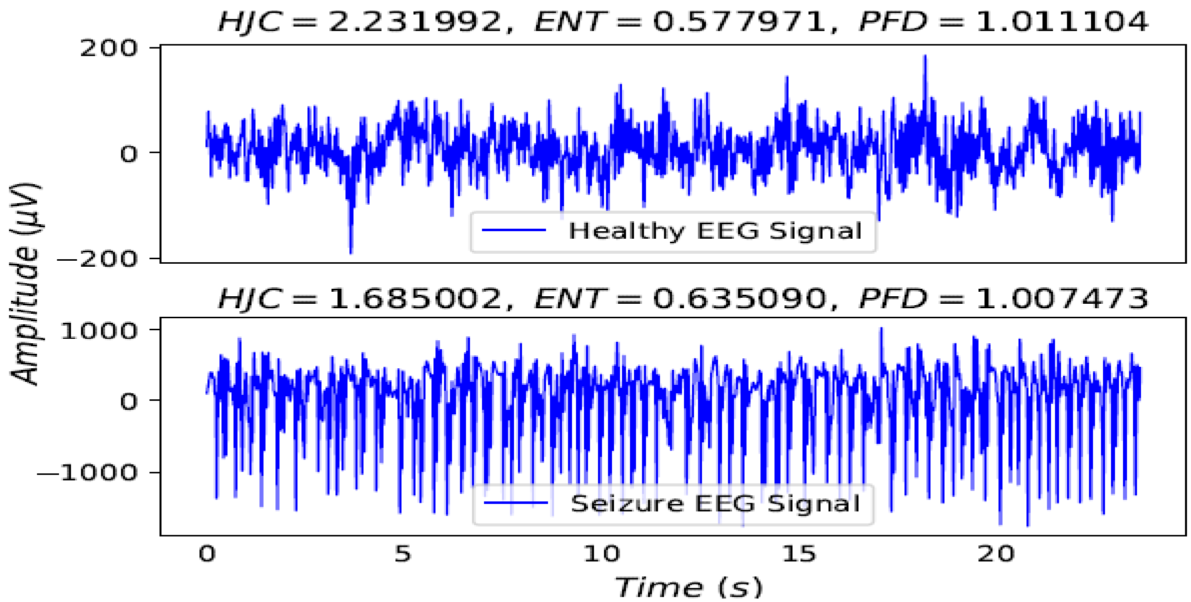
- Figure shows the plot of the Discrete Wavelet Transformation (DWT) coefficients after decomposition using Daubechies Wavelet of order four (db4).
- The final output of the decomposition is shown in the table below:

Coefficients	Frequency (Hz)
D1	43.4 - 86.8
D2	21.7 - 43.4
D3	10.9 - 21.7
D4	5.4 - 10.9
D5	2.7 - 5.4
A5	0 - 2.7

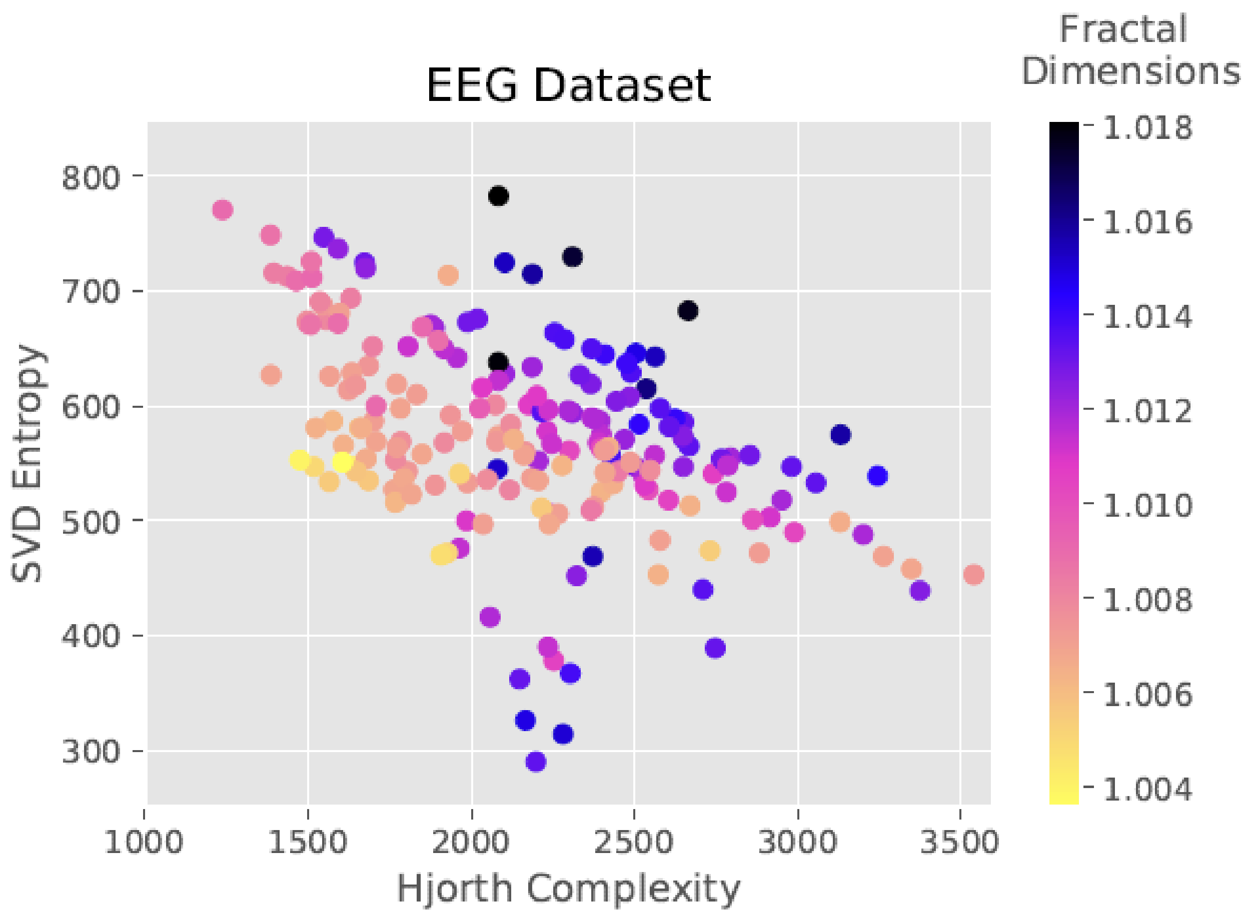


Features of EEG Signal

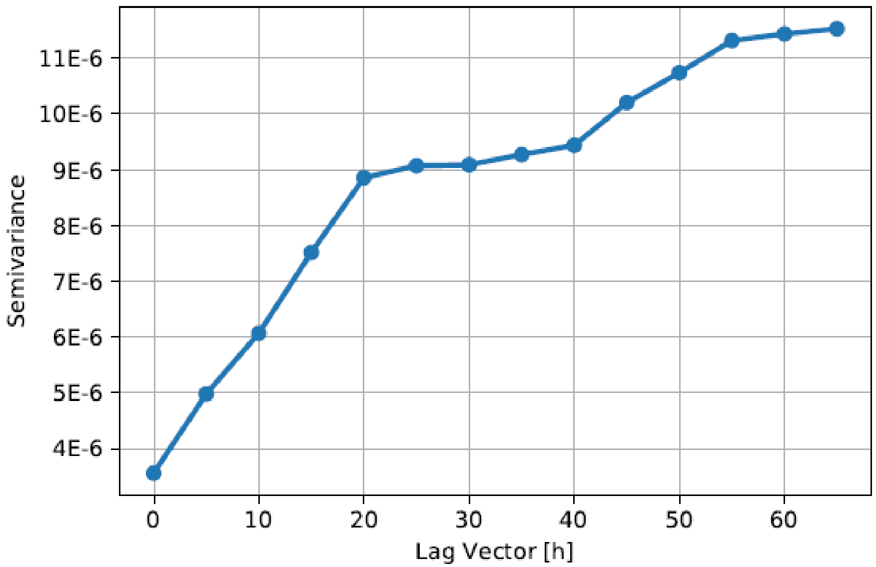
- Signal Entropy
- Fractal Dimension
- Signal Power
- Standard Deviation
- Singular Value Decomposition Entropy
- Maximum Fractal Length
- Hjorth Parameters
- Hurst Exponent
- Lyapunov Exponent etc.

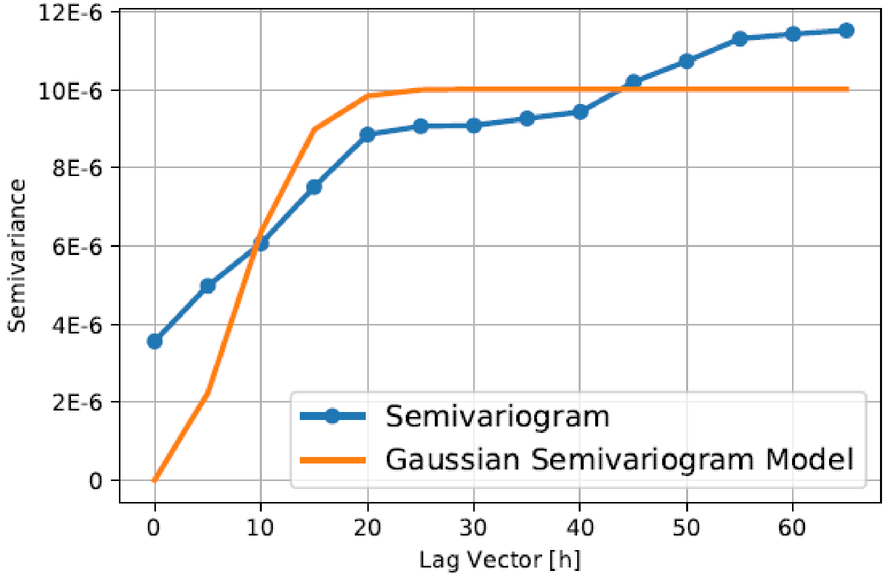


Feature Representation of Dataset

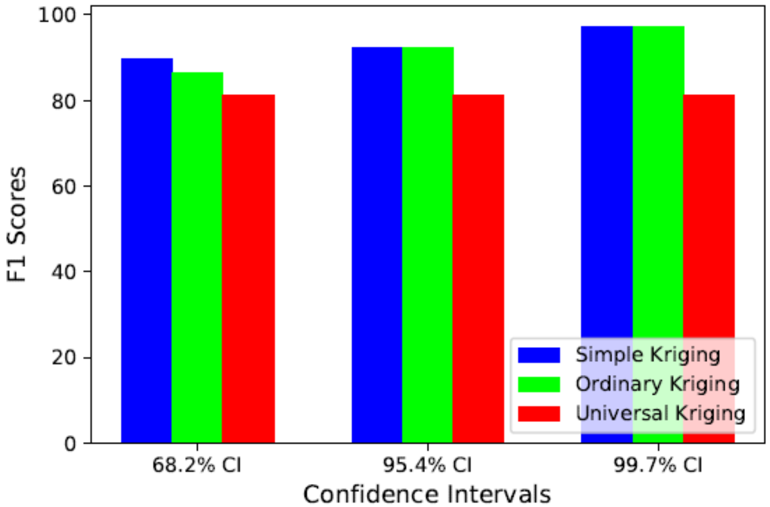


Experimental Results





Experimental Results



C. Int. (CI)	Kriging Models	Accuracy	Sensitivity	Specificity
99.7% CI	Simple Kriging	97.50%	94.74%	100.00%
	Ordinary Kriging	97.50%	94.74%	100.00%
	Universal Kriging	80.00%	89.47%	71.43%
95.4% CI	Simple Kriging	92.50%	94.74%	90.48%
	Ordinary Kriging	92.50%	94.74%	90.48%
	Universal Kriging	80.00%	89.47%	71.43%
68.2% CI	Simple Kriging	90.00%	89.47%	90.48%
	Ordinary Kriging	87.50%	84.21%	90.48%
	Universal Kriging	80.00%	89.47%	71.43%

Kriging Models	Detection Latency
Simple Kriging	**0.81s**
Ordinary Kriging	0.86s
Universal Kriging	16.25s

Comparison with Related Works

Published Works	Extracted Features	Classification Algorithm	Accuracy	Sensitivity	Detection Latency
Shoeb, et al. 2010	Spectral, temporal and spatial features.	Support Vector Machine (SVM)	NA	96.00%	4.2 sec.
Zandi, et al. 2012	Regularity, energy & combined seizure indices	Cumulative Sum (CUSUM) thresholding	NA	91.00%	9 sec.
Altaf, et al. 2015	Digital hysteresis	Linear Support Vector Machine (LSVM)	NA	95.70%	1 sec.
Vidyaratne, et al. 2017	Fractal dimension, spatial/temporal features	Relevance Vector Machine (RVM)	99.80%	96.00%	1.89 sec.
Sayeed, et al. 2019	Hyper-synchronous pulses	Signal Rejection Algorithm (SRA)	NA	96.90%	3.6 sec.
Our ICCE 2020 Paper	Petrosian fractal dimension	Kriging Classifier	100.00%	100.00%	0.85 sec.
Curr. Paper	Fract dim., Hjorth comp.& Entropy	Kriging Classifier	97.50%	94.74%	**0.81 sec.**

Conclusions

- This results in this presentation demonstrate the effectiveness of Kriging method for accurate and early seizure detection.
- The detection of seizure onset takes place in near real time with an average detection latency of 0.81 second which is better than previous models in the literature.
- Three different Kriging methods were compared for Seizure Detection and results show that Simple Kriging is a slight favorite over Ordinary Kriging while Universal Kriging is far behind them.

Future Research

- In future, we will investigate seizure prediction, which means having prior knowledge that a seizure will occur before it actually does.
- Another future research is to have unified systems that detects seizure before it happens, and then injects drug or performs other control measures right after that.
- We also intend to add security and privacy features to the overall system as it is IoMT-enabled and always connected to Internet.
- We will also use more sophisticated and power-efficient edge devices such as IBM’s neurosynaptic hardware in validating our models.

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THANK YOU